Information Disclosure in Corporate Press Releases: Implications for Stock Momentum and Volatility

Job Market Paper•

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Abstract

Using a dataset of over half a million corporate press releases, I study patterns of private information disclosures by the largest U.S. public companies. I find that the amount of positive information released by a company is positively related to both its future stock performance and future positive releases, suggesting that companies tend to ration the delivery of positive news and create sustainable price trends. This effect is stronger for firms with lower information transparency. The segmentation of positive information contributes significantly to the Jegadeesh and Titman momentum effect among winner stocks. At the same time, private information disclosures are negatively related to the arrival of public news, suggesting that releases of private information are timed to mitigate public information shocks. Accordingly, I find that stock volatility is significantly lower for firms that use reserves of positive private information as insurance against unanticipated negative events. Overall, my findings indicate a strong connection between the dynamics of asset prices and company-initiated information releases.

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Introduction

Prior literature has documented several asset pricing effects that appear inconsistent with the semi-strong market efficiency. In particular, stocks with high past returns tend to continue their strong performance in the short run but decay in the long run, the effects known as "momentum" and "reversal" (Jegadeesh and Titman (1993), Hong, Lim, and Stein (2000)). Also, companies announcing positive earnings tend to enjoy strong risk-adjusted returns for several weeks after the event, the anomaly termed "post-earnings announcement drift" (Ball and Brown (1968), Ball and Bartov (1996)). Most of the research to date has viewed these phenomena as indicative of investors' inability to price the incoming information correctly. For example, a number of studies have focused on investor irrationalities and behavioral biases that prevent investors from being able to process information objectively, thus causing their under- or overreaction to public news (Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999)).

However, it remains unclear whether the stock prices are affected as much by the investors' shortcomings as they are affected by specific properties of the information arrival to the market. In particular, little is known about how companies contribute to the return predictability effects by disclosing information in specific patterns. Consider the following two scenarios. In the first, a company reports a piece of positive news to which investors are likely to underreact. As investors realize their mistake, the stock price rises, generating a positive price trend. In the second scenario, a company possessing a lot of positive private information chooses to disclose only a fraction of it. The market reacts positively to this original disclosure. The balance of the unreported information is then released later, causing the stock price to rise again. These two scenarios are observationally equivalent, yet in the first one it is the investors' underreaction to the publicly revealed information that causes the momentum effect while in the latter it is the company's decision to make some information public while keeping the rest unreported.

In this paper I study how companies' disclosures of selected private information affect asset prices, specifically future stock returns and measures of stock risk. I use a comprehensive dataset containing press releases of the largest 1,000 U.S. publicly traded companies over a 10-year period between 1999 and 2008 to identify patterns in information delivery and investigate their contribution to return persistence effects and volatility.

I proceed with the analysis as follows. First, I construct a measure that for a given company and a given period (e.g., month or quarter) proxies for the amount of information, positive or negative, that the company released to the public via press-release wires. In every period I focus on days when the company issued press releases and construct a measure of the amount of the released private information based on stock returns on these days relative to returns on those days when no press releases were issued. The "amount" of the released information is captured by an aggregate return attributable, with certain qualifications, to press-release reports.[1] Next, I study how this measure relates to future stock returns and future releases of information.

In essence, this analysis is designed to distinguish among the following three scenarios. Consider a company that disclosed a lot of net good news over a given time period. One possibility is that these disclosures fairly reflect improvements in the company's fundamentals and no misevaluations arise as a result of them. In this case, the amount of the released information should not be associated with any specific future return pattern. The second possibility is that the company engages in an aggressive disclosure where it releases good and bad news disproportionately (e.g., by reporting all of its positive private information while concealing some of the negative) and therefore inflates its current stock valuation. In this case, the initial stock price reaction is positive, yet future returns are likely to be low as the balance of the unreported negative information will drag the price down as it leaks. If such behavior is common, it can account for the reversal effect whereby the initial price growth is followed by a subsequent price decline. Finally, it is possible that companies releasing good news are underreporting their strong fundamentals so that some balance of positive private information remains. In this case, future returns for companies releasing good news are likely to be high since the reserves of good private information, when ultimately released, will boost the price further. If such disclosure pattern is customary, then prices are likely to move in trends, resulting in the return persistence effect known as momentum.

Separately for companies releasing positive and negative information, I build a portfolio long in the quartile of stocks releasing the most information and short in the quartile of stocks releasing the least information and hold this portfolio for a number of months (3, 6, or 12) following the formation date. My results indicate that among

[1] See Section 4 for the detailed methodology.

companies disclosing positive information the top quartile outperforms the bottom by up to 7.1% per year as measured by the 3-factor alpha, the result significant at 1%. I confirm the robustness of these findings by running a Fama-Macbeth regression with cross-sectional firm characteristics as control variables. The positive return effect is three times as strong for stocks with below-median information transparency as for stocks with above-median transparency.[2] Notably, releases of positive information correlate not only with future returns but also with future positive releases. These findings suggest that companies possessing net positive information do not or cannot release it all at once and that the market is not able to infer the non-disclosed news in an unbiased manner. In other words, companies reporting more positive news are the same companies for which the unreported information is also positive.[3] This is in contrast to the theory that positive information releases signify aggressive disclosures and are associated with temporary price inflation.

However, the evidence reverses when I consider releases of negative news. In future periods, firms from the least negative quartile outperform firms from the most negative quartile by 4.1% in raw and by 4.3% in factor-adjusted return on an annualized basis. Importantly, negative information released in the current period is not a reliable predictor of either sign or quantity of future information releases. It appears that the cross-sectional variation in the amount of the released negative information is driven by different choices on how much information to release rather than by the variation in the negative information actually possessed. Companies that choose to underreport negative news experience lower (more negative) returns in future periods when previously undisclosed information leaks to the market. These results suggest that suppression of negative information is a common practice and one should beware of companies that report ostensibly minor bad news.

To establish the connection with the Jegadeesh and Titman momentum effect, I consider long-short portfolios built on the observation-period stock returns. I do so separately for companies that experienced negative returns (losers) and companies that experienced positive return (winners). In my sample, there is little overall return predictability among losers, while winner stocks exhibit borderline-significant momentum of around 3.4% per year. I consider momentum strategies for companies with high and

[2] Transparency is derived from the fraction of the stock return around earnings announcements that is realized in the run-up to the event (as opposed to the reaction return). See Section 4 on the motivation underlying this measure and the details of its construction.
[3] An iceberg analogy is appropriate: icebergs with bigger tips have bigger invisible underwater bodies.

low levels of private information releases and observe the following results. Future returns of the loser momentum portfolio do not depend on the amount of the private information released. In this case, the reversal effect found in portfolios conditional on the amount of the released information does not carry over to portfolios conditional on the overall return. However, the momentum effect among winners is largely concentrated in stocks that release more positive information. In this sub-sample the momentum profits become robustly significant and exceed 6% on an annualized basis in both raw and risk-adjusted return. These results suggest an explanation for the momentum phenomenon rooted not in investor irrationality but in the actions of companies. In particular, it appears that by rationing their good information companies can maintain a positive price trend which is not unraveled by the market.

Although these results imply that the information flow from companies contributes to return predictability, they should be interpreted with caution. First, it is unclear whether the observed disclosure patterns are strategic or even intentional. It is beyond the scope of this paper to analyze incentives that determine particular disclosure choices since these incentives are likely a combination of multiple theories (e.g., they can be linked to executive compensation, capital requirements, governance, etc.). Rather, this study focuses on the asset pricing implications of the company-initiated releases of information by examining whether a well-diversified portfolio of stocks exhibits return predictability in a specific direction. Second, one should carefully consider alternative explanations that are based on traditional investor irrationalities, i.e. propensity of investors to underreact to salient information. The most obvious concern is that the amount of the released information in the observation period is measured by the market reaction to the release. If investors underreact to this information but correct their beliefs later, this would manifest in a pattern of results similar to that described above.

To show that it is not the underraction to the original news but a series of positive releases that drives the momentum effect, I consider a number of tests. First, I note that high future returns coincide with autocorrelated positive releases. To formalize this link, I isolate periods in which the reported private information is positive but which are not followed by other periods with positive releases. For a given amount of the information released in the current period, future returns are significantly lower if the subsequent periods contain fewer positive releases. This result suggests that the continued flow of information is necessary for a price trend to persist. In the second test I separate news revealed by companies from news coming from public sources, such as news agencies

(Reuters, Dow Jones Newswires). If the return persistence is driven by investor irrationalities, the underreaction is likely to be similar whether the news is company-initiated or is created by a publicly observable event. Controlling for the article content characteristics, such as tone and quantitative score, I find that portfolios built on general newswire reports do not exhibit the same degree of return persistence as those built on press releases: the momentum profits are much lower and are insignificant in most specifications.

An important question is whether the momentum mechanism considered in this study is consistent with the semi-strong form of market efficiency. On the one hand, investors are allowed to be rational in that they are able to correctly price information which is actually made public. This is in contrast to the earlier studies that put emphasis on investors' inability or unwillingness to interpret salient information objectively (Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), Chan (2003)). On the other hand, the momentum effect is still not eliminated, suggesting that some frictions prevent the market from systematically learning about the balance of unreported private information. These frictions can be technical (e.g., some information releases are difficult to measure and quantify) or behavioral (such as ambiguity aversion whereby investors are unwilling to take bets on unobserved, allegedly concealed, information). It is also possible that a considerable cross-sectional variation in firm behavior makes it too risky to arbitrage momentum driven by selective disclosures. Although the portfolio analysis reveals significant profits, it is unclear if the standard risk-adjustment methodology is sufficient to account for this type of risk. For example, Hwang and Qian (2011) argue that ignoring information asymmetry can lead to a false discovery of anomalies that in fact represent risk premia. Since information asymmetry prevents investors from observing the unreported information, this explanation can justify the persistence of momentum arising from firm disclosure policies in the semi-strong efficient market; however, it is less suitable to explain momentum caused by investors' underreaction to publicly available information.

Finally, I study the relationship between private information releases and measures of stock risk. From the amount of the released private information and the total stock return that reflects both private and public information, I infer that on average private information releases correlate negatively with the arrival of public news. Moreover, I estimate the private-public information sensitivity for every firm in the sample and find that companies for which this sensitivity is below-median, i.e. bigger negative, have an approximately 13% lower total stock volatility. I find directionally similar but economically weaker results if I use market performance as a proxy for public news. These findings suggest that private information is mostly used as a reserve and is released to cushion the effect of (largely company-specific) public shocks. In particular, this evidence casts doubt on theories of myopic incentives which posit that managers are likely to engage in "bubble-building" (intentionally concealing negative news to boost stock growth) and "bath-taking" (disposing of negative news when the market is in downturn). Rather, my results indicate that positive private information is accumulated in good times to be used as insurance against future unanticipated bad shocks. On the whole, management of private information appears to play an important part in determining stock volatility.

Hereby I contribute to different strands of the finance literature. First, I add to the literature on asset pricing anomalies and return predictability by showing that the widely reported momentum effect can be driven by company-controlled information disclosure patterns, namely the rationing of positive information. Second, I contribute to the literature on financial media by exploring the previously under-researched connection between corporations and public media channels. Third, I contribute to the literature on price management by studying a powerful tool that allows companies to influence their stock prices. In particular, I find that the relationship between private information and returns is non-linear and that different incentives are likely at play at companies with good and bad news to report. Finally, I relate to the literature on risk and volatility and show that private information releases are timed to mitigate shocks in the arrival of public news, thus reducing stock volatility.

The rest of the paper is organized as follows. Section 2 reviews relevant literature on the return predictability, financial media, and information disclosures. Section 3 presents a framework formalizing the relationship between private information releases and stock returns. Section 4 explains the construction of the dataset and the major variables used in the analysis. Section 5 analyzes return predictability patterns as a function of the released private information and studies their connection to the momentum and reversal anomalies. Section 6 considers alternative explanations and robustness of the main results. Section 7 establishes the relationship between private information disclosures and stock risk. A brief conclusion follows.

2. Literature Review

This paper belongs at the intersection of three major topics in finance: return predictability, financial media, and selective reporting. To the best of my knowledge, this is the only study combining all of these research agendas.

The first relevant line of literature studies temporary price distortions and their subsequent corrections. In particular, since Jegadeesh and Titman (1993) discovered the momentum and reversal effects, a number of studies have attempted to explain these anomalies with traders' imperfect information processing abilities. For example, Daniel, Hirshleifer, and Subrahmanyam (1998) model the effects of overconfidence and biased self-attribution on investor behavior. They posit that investors react too strongly to their own information but tend to discount public signals. Barberis, Shleifer, and Vishny (1998) study conservatism and the representativeness heuristic and hypothesize that investors change sentiment about future company earnings based on the past stream of realizations. Hong and Stein (1999) present a model with two classes of traders with different reaction patterns to news and prices. Several studies consider more fundamental explanations of momentum. Lewellen (2002) links momentum to excess covariance in stock returns as opposed to underreaction to news. Moskowitz and Grinblatt (1999) identify a strong momentum effect in industry components that can account for much of the individual stock momentum. Ali and Trombley (2006) relate momentum profits to short sale constraints by considering a set of stock characteristics studied in D'Avolio (2002).

A number of works relate media effects and return predictability. Chan (2003) studies momentum and reversals and finds that the market underreacts to firm-specific publicly released news, yet overreacts to implicit news, implied by price changes not accompanied by any public reports. In contrast, Gutierrez and Kelley (2008) observe that extreme-return stocks with explicit news and extreme-return stocks with implicit news behave similarly, both displaying short-term reversal and longer-run momentum.

The current paper is different from these earlier studies is that it shifts focus from market frictions and investors' perception of the incoming information to companies' ability to control which information is revealed. In a sense, it assumes a weaker form of investor irrationality to explain predictability in stock returns. The market is irrational only so far as it is unable to systematically learn about the undisclosed information while being able to respond objectively to the information that actually becomes public.

The literature on financial media has studied investor behavior and stock returns in response to media publications. Fang and Peress (2009) establish the effect of media on investor participation and show that firms can reduce their cost of capital by improving their media coverage and expanding their investor base. Engelberg and Parsons (2011) demonstrate the causal effect of media on individual trading by considering exogenous events that prevent timely delivery of information to certain geographical areas. Using international data on country-wide strikes of journalists and delivery personnel, Peress (2011) finds a positive relationship between media coverage and trading volume. Also, financial media has been shown to affect the direction of trades. Tetlock (2007, 2008) measures media pessimism using General Inquirer semantic classification and finds that The Wall Street Journal columns with negative tone induce a short-lived downward pressure on the market. Examining articles about individual companies, he observes that reaction to negative tone is delayed and that a profitable trading strategy exploiting this effect exists. Several other papers make similar arguments. Dougal, Engelberg, Garcia, and Parsons (2011) exploit exogenous variations in the assignment of authors writing the market summary article in The Wall Street Journal to show the directional effect of bullish and bearish journalists on the market behavior. Feldman et al (2010) find that tone change of Management Discussion and Analysis section of Form 10-Q and 10-K adds significantly to portfolio drift returns between the filing date and the next earnings announcement.

The current study builds on this existing literature by expanding the scope of media influence in the financial market. Specifically, I examine how companies use media channels to control the spread of information to investors. A similar idea has been explored in two recent papers. Solomon (2010) finds that investor relation firms help spin positive news and generate more public media coverage for such events. Ahern and Sosyura (2011) show that by issuing a large number of press releases acquirers can temporarily inflate their stock prices during fixed-ratio stock merger negotiations and thus improve the terms of the deal. I contribute to these studies by investigating how companies' decisions to communicate private information via media channels depend on the nature of the information possessed and public signals.

Finally, the extant accounting literature investigates the prevalence and the market impact of incomplete or manipulative reporting (e.g., Teoh, Welch, and Wong (1998), Lang and Lundholm (2000), Burgstahler and Eames (2003), Kothari, Shu, and Wysocki (2009)). Crucially, most of these studies focus on hard or verifiable data, such as earnings or cash flows. However, such standardized reports are an imperfect tool for price management. First, they carry a great risk of detection so that the market learns to incorporate and discount disclosure biases. Second, they reveal realized rather than projected numbers, yet market prices are based on future expectations. Third, reporting standards are tightly regulated restricting the flow of information both in time and content thus limiting its ability to affect day-to-day prices. By using public media channels to communicate with investors, corporate managers are able to overcome these difficulties. Companies exercise discretion both with respect to the timing and the content of their press releases as well as the spin and the tone of these reports. Furthermore, as long as the firm does not broadcast apparent fraudulent news, both the market and the regulators will struggle to hold managers accountable for selective disclosures. This paper documents a set of results suggesting that discretionary releases of private information are an effective price management tool that can be used to influence present and future stock returns as well as their volatility.

3. Problem Formalization

In this section I present a simple formalization of the effects that releases of private information have on contemporaneous and future stock returns. I consider a model with two periods. In the first period, the company makes a decision about how much private information to release. In the second period, we observe the return consequences of these releases as some of the unreleased information leaks through to the market. The purpose of this section is to illustrate the dynamics of stock returns in response to the company's decision to release or conceal information. The proposed model assumes a limited form of semi-strong market efficiency, namely that investors reacts to the disclosed information but not to the information that stays private. The same results can be obtained in an extended framework that incorporates incomplete learning of past disclosure biases.

In all cases, the amount of information is measured as the percentage stock return that the release of this information would have generated. Moreover, returns are assumed additive so that a release of 50% is equivalent to the sequential releases of 20% and 30%. These assumptions make the model more intuitive while not affecting its major conclusions.[4]

At the beginning of period 1 the company possesses private information in the amount of X_0. If X_0 is positive (negative), the company is undervalued (overvalued). For convenience, I will define $D_T = -X_T$ to measure the level of mispricing; positive D_T indicates that the company is overvalued by D_T at the end of period T.[5] During period 1, the company sees the arrival of additional private information in the amount of ΔX_1 while the market observes the arrival of public information about the company in the amount of ΔY_1. During this period, some of the initial mispricing D_0 is corrected as previously private information leaks through to the market. I will assume that this correction is equal to cD_0 where c is the measure of information transparency of the firm: higher values of c correspond to greater transparency that facilitates faster private information dissemination. Finally, during period 1 the company decides how much private information to release. I denote the private information released as *PIR* and will refer to the empirical measures that are designed to capture private information releases as "PIR measures". The stock return in period 1 is

$$R_1 = \Delta Y_1 - cD_0 + PIR_1 \qquad (1a)$$

That is, the return is determined by the arrival of the new public information, the partial correction of the beginning-of-the period misvaluation, and the amount of the private information released. I assume that the company knows all parameters by the time it decides to release *PIR* so that the proper sequence of events in period T can be summarized as follows:

[4] One might challenge these assumptions with the following argument. Suppose that a company possesses private information about a $1 million cash windfall that is due to occur next period. If released today, this information would increase the stock price by 1%. However, after the stock price rises because of some other favorable information arriving at the market, the same news about the cash windfall would increase the stock price by less than 1%. While this argument is valid, it relies on the assumption that private information captures absolute rather than relative firm profitability. If the company learns that its foreign project will deliver 12% return instead of the 10% return expected by the market, this information is likely to improve market valuation by the same percentage regardless of the current stock price. In this situation, consider alternative news that increases stock price, e.g. improved earnings. These extra earnings can be reinvested at 12% creating more value for the shareholders in absolute dollars. This argument assumes that the project in question is scalable rather than a fixed NPV project. Indeed, this is most often the case in practice. Scalability of most investment opportunities makes the IRR criterion more popular among corporate managers than the NPV criterion (Graham and Harvey (2001)).

[5] I use lower case t to refer to trading days and large T to denote observation periods, such as month, quarter, or year.

1) ΔX_T and ΔY_T arrive

2) cD_{T-1} correction occurs

3) PIR_T is released

4) R_T for the period is determined

Before deciding to release PIR_1, the company sits on the private information equal to $(1-c)X_0 + \Delta X_1$. I will denote this variable χ_1; it measures the amount of private information that the company possesses before the release. The end-of-period imbalance of private information is therefore

$$X_1 = \chi_1 - PIR_1$$

Accordingly, the end-of-period mispricing D_1 can now be written as

$$D_1 = PIR_1 - \chi_1 = (1-c)D_0 + (PIR_1 - \Delta X_1)$$

That is, the new misvaluation is equal to the fraction of the old misvaluation plus the private information released in excess of what is justified by ΔX_1. Period 2 return is therefore

$$R_2 = \Delta Y_2 - cD_1 + PIR_2 \qquad (1b)$$

Notice that private information releases affect this return both directly (PIR_2) and indirectly (PIR_1 though D_1).

Next, I consider several patterns of information disclosure. In particular, it is important how companies release their private information as a function of the information they possess. Formally,

$$PIR_T = f(\chi_T) + \varepsilon_T \tag{2}$$

where ε_T is assumed to be normally distributed with mean 0 and variance V_ε, is assumed to be uncorrelated across periods, and is assumed to be independent of χ_T.

By considering different forms of f, we can formalize different hypotheses of information disclosure. For example, in the case of $f = b\chi_T$ $(0 \leq b \leq 1)$ companies release a specific fraction of their private information. In particular, if $b = 1$, an average firm releases all of its private information. If, in addition to that, $V_\varepsilon = 0$, the markets are strong-form efficient since all news are priced without error. If $b = 0$, then the decision to release information does not depend on the information available but is driven entirely by ε.

These scenarios imply different return predictability patterns for portfolios built conditional on *PIR*. Once a proper measure of *PIR* is constructed, I can test its relationship with future return and thus determine the nature of the connection between PIR_T and χ_T. To identify the testable link between *PIR* and future return, I need to evaluate $\mathrm{E}[R_2|PIR_1]$ for a given form of f. In Appendix 1 I derive the solution for the simplest case where the released information is a constant fraction of the possessed information, $f(\chi_T) = b\chi_T$, $(0 \leq b \leq 1)$:[6]

$$\mathrm{E}[R_2 \mid PIR_1] = (c + b - bc)\left(\frac{bV_\chi}{b^2V_\chi + V_\varepsilon} - 1\right)PIR_1 \tag{3}$$

where V_χ and V_ε stand for variances of χ_1 and ε, respectively.

An important empirical question is: what does it mean to observe a company that is releasing a lot of (net positive) private information? Does it mean that the firm is reserving good information by revealing its true state incompletely or that it is creating

[6] The solution is based on the projection theorem that requires normality assumptions. This restriction means that, generally speaking, for non-linear functions f the exact expression for the conditional expectation cannot be obtained. However, simulations reveal that the linear minimum mean square error (LMMSE) estimator can still be used with reasonable accuracy resulting in similar directional conclusions on the relationship between *PIR* and future return.

a misvaluation by releasing information in excess of the justified amount? In the former case, we should expect high returns to persist while in the latter they should reverse. Both of these scenarios are modeled by (2) but they correspond to different levels of V_χ and V_ε. If most of the variation in *PIR* is explained by the variation in ε, then high private information releases are inflationary phenomena. For example, suppose that during certain corporate events, such as secondary equity offerings and share repurchases, all companies attempt to either embellish their prices or keep themselves undervalued. Assume that these events are distributed randomly over time. In this case, the occurrence of such an event would correspond to a certain realization of ε (e.g., high positive for share issuances and high negative for share repurchases). Whatever the event, the price is temporarily distorted and should correct to its fair level in later periods. If this pattern is dominant, then high-PIR firms, those that experience a high realization of ε, should underperform low-PIR firms as time passes. However, if *PIR* is mostly driven by χ_T rather than ε, i.e. $V_\chi >> V_\varepsilon$, observing high-PIR firms means observing firms with high levels of positive private information. In this case, high-PIR firms will outperform low-PIR firms in future periods because high-PIR firms, while revealing more positive private information in period 1, are at the same time more undervalued due to the undisclosed fraction of the positive information.

This intuition is formally confirmed by the formula in (3). When b is 0 or when ΔX is the same across all firms, *PIR* is never a signal of the private information possessed by the company but is a signal of temporary misvaluation. In this case, the model predicts that high-PIR firms will experience lower future returns since the coefficient in front of PIR_1 is negative. On the other hand, if V_ε is 0, *PIR* is a perfect signal of the growth prospects. Companies with higher *PIR* and better prospects will experience higher future returns.

For the empirical sections of this paper, it is important to consider scenarios where function f is non-linear. In particular, we should allow for a possibility that companies treat their positive and negative information differently. The analysis of these cases will require considering piece-wise functions f with a kink at 0. In the empirical tests, this would correspond to building *PIR* portfolios separately for firms with positive and negative χ_T. However, since χ_T is unobservable, I will consider companies with positive and negative PIR_T instead. Although a company with positive *PIR* is not guarantied to have positive χ because of the noise generated by ε, it still has a higher chance of having positive than negative χ. In other words, a splitting point based on *PIR* is the best guess of a splitting point based on χ. In practice, it is unlikely that firms with negative private information χ will be able to release a lot of positive information *PIR*, suggesting that a sign of *PIR* is a good approximation for the sign of χ. Following these arguments, I will assume that formula (3) is valid for companies reporting positive and negative information, albeit with different parameter values that result in different future price paths.

4. Data and Methodology

I begin constructing my dataset by considering all public U.S.-domiciled companies that have appeared in the top 1000 by market capitalization at any time (at the end of the year) between 1999 and 2008. There are 2,045 of such companies as per CRSP files, from which I retrieve all relevant trading data. For each such company I obtain a Factiva intelligent indexing code by searching for the company name in Factiva. Codes are assigned by Factiva to assist in finding articles that mention a specific company in a meaningful context. In those cases where code assignment is ambiguous, e.g. when different codes identify the same company over different time periods, I analyze several articles returned by the Factiva engine to determine the proper correspondence. I eliminate company-years for which the Factiva-CRSP link cannot be reliably established. This often happens when a company undergoes restructuring, such as M&A, and the current Factiva code assigns articles on both the target and the acquirer to only the acquirer. In the end, I am able to obtain reliable intelligent indexing codes for 1,544 companies.

Once the codes are in place, I use them to submit queries to the Factiva website and download articles returned by these queries. Factiva offers several options to narrow down the list of sources. I am searching for all sources that are categorized under “Major News and Business Publications”, “Press-release Wires”, and “Reuters Newswires”. In addition, I limit my search to all articles in English that appeared between January 1999 and December 2008 inclusive. For the main analysis of this paper, I focus on press releases (PR) and Reuters newswires (NW) for which I require adequate coverage. Some companies are covered sparsely by Factiva or the coverage is concentrated in specific periods. In such cases, I eliminate the company altogether if the earliest and the latest press-release or newswire article in the sample are separated by less than 365 days. Finally, I require that a company be present in both the press-release and the newswire sample. After applying these filters, I end up with the main dataset of 1,122 companies or 34,212 company-quarter periods.

In addition to the text of the article, I am able to obtain information about the exact date and time of publication (where indicated), the author of the piece (if applicable), the number of words in the article, the name of the source (e.g. “The Wall Street Journal”), and the title. After the download, I eliminate duplicate articles. Articles are considered duplicates if they share the same source, title, date, and time of publication. I further eliminate articles that contain empty bodies or for which the number of words is smaller than 5.

Although Factiva reports the date of publication for each article, this date is not always relevant for my analysis. Since my goal is to match an article to the market return that can be attributed to the information contained in the article, I need to reassign dates in such a way that all articles appearing on day t but after the market closure would correspond to the next trading day. Figure 1 shows the distribution of the publication time for press releases and newswires. As expected, most articles come out during the trading hours. Interestingly, the appearance of press releases is concentrated at round hours such as 8:00 am or 9:30 am. In contrast, we can detect no such pattern among Reuters newswires. This observation is consistent with the idea that while companies exercise considerable freedom on when to issue a release and often choose convenient time to do so, newswires are more likely to reflect the actual time of the news arrival. All articles that appeared on trading day t between 0:00 am and 3:59 pm EST are assigned to day t as a reaction day. All articles that appeared between 4:00 pm and 23:59 am are assigned to the next trading day as indicated in CRSP. If t is not a trading day, then all articles appearing on that day are assigned to the next available trading day (e.g., news published on Friday evening are matched to next Monday’s stock performance). Henceforth, “the publication day” or “the reaction day” will refer to the same date assigned by this procedure.

Next, I classify each day into either a press-release or a newswire event. This separation allows me to identify two classes of news: one largely controlled by companies and the other distributed by news agencies (in this case, Reuters). The format and timeliness of these articles are similar, yet a press release is the origination point for all information that a company chooses to release, while a newswire contains original information on public events whose occurrence the company cannot control. I assume that days with press releases but no newswires are dominated by company-initiated disclosures. However, major press releases are likely to be followed by newswire articles which contain the same message. The opposite can also be true: a company can be forced to issue a same-day press release in response to a piece of news reported in a newswire. To deal with these issues, I classify a day as a PR (NW) event if the first article published on that day is a press release (newswire). In this case, I assume that the first article contains the most relevant information and thus the return on this day reflects more of the information revealed in that article than all subsequent articles. This assumption is plausible since publications tend to occur in clusters with the first publication containing the most important original piece of news. To the extent that there is noise in this classification procedure, it should work against my finding significant results, especially those that differ between press-release and newswire events.

In the end, all trading days of any time period are divided into PR events, NW events, and no-events, i.e. days that don't contain either a press release or a newswire. Additionally, I eliminate all events that appeared in the (-1,1)-window of any earnings announcement day as per COMPUSTAT to ensure that my results are not driven by the effects documented in the earnings announcement literature. My final dataset contains 519,865 press-release articles and 420,079 newswire articles. These represent 256,796 press-release event-days and 167,300 newswire event-days. I further classify each event-day as positive (negative) if the market-adjusted return on that day is positive (negative). The market return is the return on the CRSP value-weighted index.

Figure 2 depicts historical prevalence of press-release and newswire articles and events. The number of press releases and the fraction of PR days in a quarter increased nearly fivefold following the Fair Disclosure Act of 2000 which made press releases a primary means of communicating timely information to investors. In contrast, the prevalence of newswires declined somewhat in the first part of the sample period but remained fairly stable in the last 5 years.

Table 1 reports some summary statistics pertaining to returns on event and no-event days. Both PR and NW event returns are bigger in absolute magnitude than no-event returns. On a positive (negative) PR day, the stock price grows on average by 1.81% (drops by -1.67%). This is in contrast with the no-event average price movements of

1.65% (-1.53%) and NW event price movements of 1.85% (-1.75%). In addition, the returns are more dispersed on news days. For example, the standard deviation is 2.40% (2.23%) for PR positive (negative) events and only 2.12% (1.87%) for no-event positive (negative) days. On average, there are 7.51 PR days in a quarter and 4.89 NW days. Conditional on the day being a PR (NW) event, the average number of articles of that type appearing on that day is 2.02 for PRs and 2.51 for NWs. PR (NW) articles contain on average 738.96 (395.78) words although some articles are big and exceed 10,000 words. Panel B of Table 1 shows the distribution of Factiva-reported subjects for a randomly chosen 5% of PR and NW articles by either the frequency of occurrence or the magnitude of return on the day of the reaction.[7]

Next, I construct the main variable of interest that would proxy for the private information released (PIR) as defined in the previous section. On any PR day the stock return is a combination of the return that can be attributed to the information contained in the PR and the return that is driven by other information arriving at the market. To separate the two, I approximate the average daily return in the absence of events as

$$Rpublic_t = (\text{cumulative return over no-event days})^{1/N_0} - 1$$

where N_0 is the number of no-event days in the period. Then I calculate the return attributable to the information contained in the press releases on a PR day as follows

$$Rprivate_t = \frac{1 + Ractual_t}{1 + Rpublic_t} - 1$$

where $Ractual_t$ is the actual stock return on day t. Effectively, all non-event days of the period are treated as benchmark days to which a PR day is compared.[8] Therefore if a stock commands a higher premium which is unrelated to information disclosures, this premium will be netted out of the calculation and will not affect the PR-driven return.

[7] Technical difficulties prevent collection of these subjects for all PR and NW articles.

[8] My main results are unchanged if I include NW event-days in the calculation of *Rpublic*. On average, 80% of days in the period are no-event days.

Finally, measure PIR of the amount of private information revealed through press releases during the whole period T is defined as

$$PIR_T = \prod_{t \in T} (1 + Rprivate_t) - 1$$

where return is cumulated across all PR events of period T.

Unlike a simple cumulative return across all PR days, this measure is not mechanically related to the total stock return during the period. Rather, it represents the decomposition of that return into the return driven by the PR information and that which would have occurred in the absence of that information. If the total return in the period is largely driven by the releases of private information, then PIR_T will high explanatory power for R_T. On the other hand, if the company releases good private information during periods when there is a lot of bad public information, R_T would be driven by public news and could be negatively related to PIR_T. It is therefore important that I do not take the total daily return on a given PR day as a proxy of private information released on that day but only assume that this return incorporates the reaction of the market to that information while also reflecting any other information arriving on that day.

Another attractive property of the PIR measure is its independence of the number of articles. In many of the previous studies on the financial media (Fang and Peress (2009), Ahern and Sosyura (2011)), the number of articles has been taken as a proxy of media influence. However, this approach is problematic for two reasons. First, the number of articles depends heavily on company size: larger companies attract more media coverage. Controlling for this effect is not a trivial matter since this relationship is non-linear. Second, the same amount of information can be strategically partitioned by companies into several articles that appear on different days. In this case, the amount of information delivered on each day will be small but the number of media events will be big. The opposite can also be true: companies can pool important information and distribute it in one big release. The measure of information based on the number of articles will fail to pick up these nuances. For these reasons, I devise a measure that proxies for the total amount of the information released based on the market reaction to the PR reports as opposed to their frequency.

To achieve reasonable accuracy of measurement, I require a sufficient number of days to estimate PIR. For this reason I calculate PIR_T at quarterly and semiannual frequency and conduct my analysis at quarterly and semiannual intervals. Each half-year period covers months from January to June or from July to December. To ensure that my analysis is not affected by extreme observations caused by noisy adjustments, I winsorize PIR_T by eliminating days that fall in the top or bottom 1% of all PR events in a given quarter or half-year. Panel A of Table 1 reports summary statistics on this private information measure and other return-based variables at quarterly frequency. The average level of PIR across company-quarters is 0.34%, six times as low as the average return. Even though the median number of event days in the quarter is 3, the median of PIR_T is 0 because PIR_T assumes both positive and negative values.

Finally, I construct several variables that are used either for interaction effects or as controls. The most important of these is a proxy for information transparency of a firm. Prior literature has used size, trading volume, Amihud illiquidity, or analyst dispersion as proxies for information transparency or asymmetry (e.g., Zhang (2006)). None of these are very useful for this study. First, because my sample consists of big and liquid stocks, it is unlikely that informational transparency will depend on size and volume as much as it depends on them in the general population of stocks. It is even possible that some big firms with complex operations and multiple divisions have lower informational transparency as the market struggles to incorporate such diverse information correctly. Second, I look for a measure that would closely correspond to parameter c in the model, i.e. would proxy for the speed at which private information leaks through. It is not clear how well the popular measures of transparency fit this requirement. Therefore I construct my own measure of transparency in accordance with the declared objectives. I measure the ability of the market to learn inside information about a given company by calculating how much of the return around earnings announcements made by this company can be attributed to the run-up. The smaller the market surprise on the announcement day relative to the run-up, the higher the information transparency of the firm. For each company-announcement in my sample, I calculate "run-up" as the cumulative stock return over days -10 to -1 relative to the announcement date. I then calculate the overall announcement effect as the cumulative stock return over days -10 to 10. The information transparency measure for that firm is computed as the average across all earnings announcements of the ratios of the run-up return to the overall announcement return. To mitigate the issues of the noisy estimation, I consider a dummy variable based on this measure. The information transparency dummy $infotransp_{jT}$ is defined as 1 if the company is above the median by information transparency among all the companies in my sample in the considered period and 0 otherwise.

Other variables used in my analysis are defined as follows: $numPRs_{jT}$ is the number of press-release articles issued by company j in period T divided by 100; $fraceventdays_{jT}$ is the ratio of the number of event days for company j in period T to the total number of trading days in that period; $size_{jT}$ is the log of company j's market capitalization in 000 at the end of period T; $BtoM_{jT}$ is the ratio of the total book equity of company j to its market capitalization at the end of period T; $illiquidity_{jT}$ is the percentile rank of the Amihud illiquidity measure for stock j calculated over the trading days of period T, $instownership_{jT}$ is the number of shares held by institutional investors whose portfolios are reported in Thompson 13f database to the total number of shares outstanding of company j at the end of the year preceding the year that contains period T; $volume_{jT}$ is the average monthly dollar volume of company j in period T.

Although the number of articles and the PIR measure are conceptually independent, they can still be related if companies consistently prefer disclosing information in fixed amounts. For example, if we assume that every PR report is likely to contain the same amount of information, then the absolute value of PIR should be positively related to the number of press releases. In Table 2 I investigate the relationship between PIR (signed and absolute amount) and the media activity of the company as measured by the number of PR reports in the period and the fraction of the PR days. Loosely speaking, PIR is equal to the average PR day return (adjusted for the public information) times the number of PR days in the period. The evidence in Table 2 helps to determine which of the two components affects PIR more significantly.

The results indicate that PIR is positively related to the number of press releases meaning that this number as a proxy for information would successfully capture releases of positive information. However, this would be a coarse measure since the economic significance of this result is not very strong: as the number of press releases grows by 100, PIR only increases by about 1%. The relationship between |PIR| and the number of press releases is stronger, confirming the intuition that more information is released when more PR articles are issued. Likewise, there is a robust positive relationship between |PIR| and the fraction of the event days in the period: an increase in this fraction by 0.1 would correspond to an increase in the total private information released by 2.2%-2.3%. There is no significant relationship between PIR and the average return on a PR day (unreported). This result implies that the average event-day return in the period is not a good proxy for the overall amount of the released information. To summarize, the amount of the released information appears to be driven more by the number of events than by the significance of an average event.

It is also apparent from Table 2 that |PIR| is negatively related to size, positively related to the book-to-market ratio, positively related to volume, and negatively related to the information transparency of the firm. The results on size and information transparency can be explained by the fact that bigger and more transparent firms find it difficult to conceal information in the first place, so their press releases are less likely to contain information that the market does not yet possess. Positive association with volume implies that trading intensifies when more private information is released, the result consistent with multiple studies on trading volume around earnings announcements. The link between PIR and the book-to-market ratio is more difficult to interpret. It is possible that undervalued firms with high value of the ratio are able to release more positive information and thus improve their valuation.

5. Return Predictability as a Function of Released Information

5.1 Portfolio Analysis

I now proceed with the main analysis and test implications of PIR for future stock returns. I construct portfolios conditional on PIR in the following way (similar to Jegadeesh and Titman (1993)). For each company-month I calculate PIR over the past 3 months or the past 6 months, referring to these as quarterly or semi-annual observation periods, respectively. I split the sample into positive and negative PIR and sort stocks by PIR into four equally weighted portfolios of stocks within each subsample. Then I focus on the portfolio long in the top quartile and short in the bottom quartile. This portfolio is held for 3, 6, or 12 months and then rebalanced. At any month, the return on the trading strategy is the average of returns of portfolios formed in the last 3 months or the last 6 months. The analysis is conducted for all stocks in the positive and negative PIR sample as well as separately for stocks with below- and above- median information transparency.

Table 3 reports the results for quarterly (Panel A) and semi-annual (Panel B) observation periods. The major conclusion is that the relationship between PIR and future return is non-linear and takes opposite signs in the negative and positive PIR subsample. Among negative PIR stocks the reversal effect is apparent: in the 3 months after the quarterly formation the long-short strategy delivers an average negative monthly return of -0.33% (monthly alpha of -0.35%). These represent -4.03% and -4.28%, respectively, on an annualized basis. The numbers are somewhat smaller for semi-annual formation, yet they remain statistically significant at the 10% level or higher. In all specifications the reversal effect fades with time. For example, if one holds the long-short portfolio for 6 (12) months instead of 3, the average monthly return drops in absolute magnitude from -0.33% to -0.28% (-0.25%). For semi-annual observation periods the long-horizon returns or alphas are no longer significant.

These results imply that high (less negative) levels of PIR observed at times when the overall released information is negative is indicative of price inflation. One possible interpretation is that companies forced to report negative news are likely to underreport information, possibly in an attempt to avoid big price crashes or in hope that some of the damage can be repaired with time. The information released might be the one difficult to conceal, so we still observe negative reactions to these press releases as opposed to neutral reactions. As the bad news seeps through to investors, companies that chose to release more bad information (big negative PIR, the short part of the portfolio) outperform those that chose to release less (small negative PIR, the long part of the portfolio). Consistent with this explanation, the effect is stronger at short horizons, when most of the correction occurs, and abates later, when more information becomes incorporated into prices.

In stark contrast to these results, companies that release positive information exhibit momentum. Moreover, the momentum effect increases with the holding horizon. The portfolio long in high positive PIR stocks and short in low positive PIR stocks delivers an average monthly return from as low as 0.27% per month (if it is held for 3 months) to as high as 0.39% per month (if it is held for 12 months). The alphas of this strategy are even bigger ranging from 0.37% to 0.52%, all significant at the 5% level or higher. The most profitable strategy is to buy the long-short PIR portfolio formed on the levels of PIR measured over the preceding 6 months and hold it for a year after the formation.

This strategy will earn an average raw return (alpha) of 5.03% (7.06%) until the next rebalancing date.

These results suggest that companies with positive information do not or cannot release it all at once. Companies that release a lot of good information are those that also possess a substantial unreported balance of positive information that will leak to the market in future periods. The fact that the momentum effect does not subside with the length of the holding horizon confirms that it is driven by solid fundamental data that becomes known to the market and not by temporary mispricing phenomena. This finding further supports the argument that companies releasing high amounts of positive information are less likely to have inflated prices and more likely to be undervalued.

Next, I study how the relationship between PIR and future return differs between the low and the high information transparency sample. The evidence in Table 3 indicates that information transparency has little effect on the reversal among negative PIR stocks. Even though low transparency stocks appear to experience stronger reversals in the next 3 months, this effect is neither economically big (-0.36% monthly vs -0.27% monthly) nor robust across different horizons. These results can be explained by the conflicting effects that transparency has on the stocks of underreporting companies. On the one hand, more transparent firms might struggle to conceal information in the first place thus experiencing lower initial misevaluation and higher future returns. On the other hand, transparent firms are less likely to prevent negative information from being revealed in future periods. The revelation of this information can result in lower future returns.

However, the effect of transparency on positive PIR stocks is strong and unambiguous: the momentum is largely concentrated in the subsample of companies with below-median transparency. For example, the long-short portfolio of stocks with below-median transparency held during 6 (12) months earns an average monthly return of 0.56% (0.54%) compared to an average monthly return of 0.14% (0.20%) for stocks with above-median transparency. The alpha differentials are also sizable: the long-short low-transparency strategy outperforms the long-short high-transparency strategy by 0.48% (0.72% – 0.24%) per month if both portfolios are held for 12 months after the formation. One interpretation consistent with these results is that high transparency companies find it more difficult to ration positive information and keep a part of it hidden. Therefore, high PIR in these firms does not necessarily signal better prospects but can be a fair representation of the current private-public information imbalance.

5.2 Regression Analysis

Next, I perform a regression analysis of the relationship between PIR and future returns. While the portfolio approach offers some advantages, such as quantifying the economic effect and allowing overlapping measurement periods, it has limited capacity to control for cross-sectional characteristics of firms some of which were shown to be related to PIR (see Table 2). Therefore, I complement the portfolio results with the evidence from the Fama-Macbeth regressions.

I regress stock return in quarter $T+1$ on PIR measured in quarter T, its interaction with the information transparency measure, and control variables. To match the portfolio approach, the slopes are allowed to be different between negative and positive PIR stocks. To fit a continuous piece wise linear regression, I define variables *PIRneg* and *PIRpos* as follows:

$PIRneg = PIR$, if $PIR < 0$ and 0 otherwise

$PIRpos = PIR$, if $PIR \geq 0$ and 0 otherwise

The results in Table 4 confirm the non-linearity: the slope is strongly negative for negative PIR stocks and is strongly positive for positive PIR stocks, both results significant at 1% after the inclusion of controls. An increase of 10% in the PIR of a negative-PIR (positive-PIR) stock is associated with a decrease (increase) in the stock's next quarter return of 1.25% (1.40%). The coefficient on the interaction of PIR and the information transparency measure is positive but insignificant for stock-quarters with negative PIR and is negative and significant at 5% level for stock-quarters with positive PIR. The next-quarter momentum in response to a 10% increase in this quarter's PIR drops from 1.85% for above-median transparency stocks to 0.65% (1.85% – 1.21%) for below-median transparency stocks. These results are generally consistent with the evidence documented in the portfolio analysis except for the magnitudes of the incremental effects which are somewhat smaller in the regressions.

In the same Table 4 I test the relationship between current and future information disclosures. The results indicate that disclosure activity of negative PIR firms is not significantly autocorrelated while positive PIR firms continue to report positive news in future periods. This effect is significant at 5% across all specifications. These results are consistent with the hypothesized behavior of companies during periods of distress and prosperity. The unreported fraction of negative information is more likely to eventually leak on its own rather than be voluntarily disclosed by the company in a formal press release. However, companies rationing positive information take active action in revealing this information thus creating a positive correlation between current and future PIR.

When interpreting the results of this chapter, it is important to remember that PIR is not an objective measure of the importance of the revealed information but is the market reaction to the disclosure. As such, the tests proposed here are effectively joint tests of the information rationing or concealment and of market's inability (or imperfect ability) to recognize this behavior. A transparent firm engaging in information rationing is less likely to register high future returns since PIR for this firm contains a fraction of the information that is physically unreported but is already priced by the market. These considerations imply that information rationing might in fact be more prevalent than the results indicate, yet some of it is unmeasurable due to the market's facility in pricing these effects from the beginning.

It is also important to acknowledge that the analysis of this chapter does not establish causes for the documented disclosure patterns. In fact, it is possible that information releases are not even driven by financial incentives but are determined by competition and marketing factors. It is also possible that companies do not conceal the already known positive information but in fact generate autocorrelated positive signals, e.g. by releasing limited functionality products and adding advanced features later. Therefore, "information rationing" should be treated as an empirical phenomenon consistent with but not exclusive to deliberate price management strategies.

5.3 Link to Jegadeesh and Titman effects

Previously, I used terms "momentum" and "reversal" to describe return predictability patterns as a function of PIR. However, these need not be related to proper momentum and reversal effects documented in the asset pricing literature started by Jegadeesh and Titman (1993). These effects require that portfolios be built conditional on levels of past return and not on levels of PIR. It follows from equation (1) that PIR can explain a portion of the total return. If this portion is large enough, we can expect the proper momentum-reversal to be driven, at least in part, by the information disclosure patterns documented here. However, it is also possible that these effects are largely driven by market over/under reactions to other components of the total information, such as public information. Prior literature has devoted considerable attention to these explanations of the momentum-reversal anomalies (Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), Chan (2003)).

In this section I study the relationship between momentum portfolios proper and the effects of information disclosures. I build portfolios conditional on past return (R) for different levels of PIR as well as for different levels of PIR/R, where PIR/R is defined as PIR^+/R if $R>0$ and PIR^-/R if $R<0$, where PIR^+ (PIR^-) is a measures of private information released on positive (negative) PR events only. I proceed as follows. In each month, I separate stocks into those with negative observation period return (losers) and positive observation period return (winners). For this analysis, the obsefvation period is 6 months preceding the portfolio formation date. Both winners and losers are then sorted into two equal groups by the released private information in the observation period (PIR) or the ratio of this measure to the stock return in the period (PIR/R) and four quartiles by the observation period return (R). Sorting on PIR or PIR/R is conducted independently of sorting by R. The long-short portfolio is defined as the portfolio long in the top performance quartile and short in the bottom performance quartile. This portfolio is held for 3, 6, or 12 months. At any month, the return on the strategy is the average of returns of long-short portfolios formed in the last 6 months.

The average returns and 3-factor alphas of these trading strategies are reported in Table 5. First of all, unlike in the case of negative PIR stocks, there is no significant reversal effect for negative-R stocks (losers). Although the long-short portfolios deliver mostly negative returns, these are never significant. Splitting by either PIR or PIR/R does not make a difference: in either group we cannot detect a consistent pattern of significant future-period returns. The results are different for positive-R stocks (winners). Both low and high positive PIR stocks exhibit momentum. However, this effect is twice as strong for above-median PIR firms as for below-median PIR firms. Over the three months holding horizon the future average monthly return gap between strong and weak performers is 0.28% (insignificant) for low PIR firms and 0.55% (significant at 5%) for high PIR firms. The results are similar but slightly weaker when the stocks are sorted on the basis of their PIR/R ratio.

It is interesting that momentum trends of low and high PIR firms tend to converge over longer holding horizons as the momentum of high PIR firms slows down, dropping from 0.55% to 0.27% per month when one switches to the 12-month holding strategy. This result suggests that information rationing indeed contributes to the Jegadeesh and Titman momentum but only at short horizons. There appears to be some residual, albeit weak, component of momentum that persists at longer horizons in both the low and the high PIR subsample.

Table 6 mimics the portfolio analysis in a regression setting. As before, I fit a continuous piece-wise linear regression which allows different slopes for loser and winner stocks. Here, the interaction terms show how the momentum effect changes as a function of the information management variable. The evidence confirms major findings of the portfolio analysis: all interactions with *Rneg* are insignificant while the interactions with *Rpos* are significant and positive both for PIR and the PIR/R ratio.

Overall, this section lends evidence to two important conclusions. The first is that a strong PIR-reversal effect found in portfolios conditional on negative PIR does not carry over to portfolios conditional on past return. This is hardly surprising given that most return-reversals found in the literature are weak, are usually observed at longer horizons, and are often interpreted as a correction to momentum. The second conclusion is that there appears to be a strong link between the proper return momentum and future performance of stocks that release a lot of positive private information. This link suggests an explanation for the momentum anomaly that is rooted not in investor irrationality but in private information disclosure policies. This explanation does not rely on market inefficiency as much as most behavioral arguments do. The only required condition is that the market incorporates all available information while being unable to draw reliable conclusions about the information that is yet to be released.

6. Robustness and Alternative Explanations

The results in the previous section suggest that a string of positive information disclosures are associated with a sustained momentum, yet they cannot be interpreted as conclusive evidence that a series of positive releases create this effect. In particular, investors' underreaction to the original signal can result in a similar pattern of future returns with or without follow-up information events. The fact that momentum is accompanied by the autocorrelation in positive releases corroborates the argument that company-initiated information flow is responsible for the return persistence, however a more formal test of this relationship is in order.

To conduct such a test, I focus on periods (quarters or half-years) for which the amount of the released information PIR is positive. I further split this sample into periods that are followed by another period with highly positive releases and periods that are followed by a period when no significant information was released through PRs.[9] For every company, a high positive release period is defined as a period in which the amount of positive information released is above median for the whole time series for that company while no-event periods are periods where this amount is below median. The results of this test are reported in Table 7. The evidence of momentum is much stronger (by a factor of 2-2.5 in terms of economic magnitude) when more positive information is released in the next period, confirming that a series of positive releases is instrumental in creating a sustainable price trend. In contrast, original releases of the same magnitude that are not followed by other positive releases do not trigger the same effect, suggesting that investors' underreaction to the original news is unlikely to create return persistence without the continued flow of information. At the same time, similar analysis conducted over the sample of periods with negative disclosures does not reveal the same return disparity between cases when the next period has a high negative PIR and a low negative PIR.

To further separate explanations rooted in pure investors' underreaction from those based on firm behavior, I consider a falsification test based on the sample of newswire (NW) events as defined in Section 4. While these articles are structurally similar to press releases in that they distribute timely information reaching a wide base of sophisticated

[9] This analysis does not represent an actual trading strategy since it utilizes information about future periods (in this case, future PIR). Rather, this analysis is provided for comparison with Table 3 which is based on the classical portfolio approach.

investors quickly, they are likely to differ on the point of information origin. In particular, any information released by a company will be registered in a press-release wire first while any major publicly observable event unanticipated by a company will initially appear in newswires. The intuition behind this test is as follows: if the momentum effect results from investors' underreaction to salient information, we should observe similar return persistence whether the information event is based on a press release or a newswire.

For the purposes of this analysis I construct a measure (called NIR) of information contained in newswire articles over a time period. I follow a methodology similar to that of PIR but use newswire days as information events. Then I rerun the portfolio analysis from the previous section using the NIR measure and report the results in Table 8. The evidence in Panel A (it can be directly compared to Table 3) indicates that future returns from the NIR strategies are much weaker than those from the PIR strategies, are only borderline significant for periods with positive information, and are never significant for periods with negative information. Panel B of Table 8 (it can be compared to Table 5) shows momentum profits conditional on the level of NIR. In contrast to PIR, which enhances the momentum effect, NIR has little overall impact on momentum returns. The evidence of small positive returns for winner stocks is present in both low and high NIR subsample, suggesting that investors' reaction to newswire-distributed information does not drive future returns.

One potential concern is that press releases and newswires are not directly comparable since they contain information of a different nature. For example, it is plausible that press releases contain more verbal descriptions to which investors are more likely to underreact. This explanation could account for the apparent difference in profitability of PIR and NIR strategies and would be consistent with investors' irrational reaction to observable information. To control for differences in the type of information I employ three variables: the length of the article (a proxy for the total amount of information), the quantitative score calculated as the percentage of numerical symbols (a proxy for whether information is numerical or descriptive), and the positive/negative tone calculated as the ratio of positive/negative words in the article to the total number of words (the classification of words is as per Loughran and McDonald (2011)). Press releases are likely to be slightly longer than newswires (an average length of 739 words vs 396 words), are similar in quantitative score (2.80% vs 2.95%), and are more likely to express positive tone (0.98% vs 0.64%) and less likely to express negative tone (0.66% vs 1.52%). Tone of media publications has been shown to affect investors' reaction (Tetlock (2007, 2008), David et al (2007)). However to the extent that this effect is present in the current sample, it would only strengthen my main conclusions since positive tone of press releases should cause initial overreaction to positive information and lower future returns. Nevertheless, to ensure that the differences between PIR and NIR strategies are not driven by the differences in article characteristics, I build recombined portfolios by first sorting the observations on an average article characteristic in the period, then within each characteristic quartile sorting by PIR or NIR, and finally pooling all lowest (highest) PIR or NIR quartiles together to form the recombined lowest (highest) quartile. The results of this analysis (unreported) are similar to those presented in table 3, 5, and 8.

Another possible explanation for persistent return and autocorrelation in positive releases is investors' active reaction to repeated news. For example, investors can underreact to the original press release but adjust their beliefs when the follow-up report with the same information comes out. To understand whether momentum is associated with a string of press releases of the same informational content I perform the following analysis. For every company and every two consecutive periods I measure their informational overlap as the ratio of common words between press releases of the current and the next period to the total number of words in all press releases over these periods. For each company I split the sample into periods that are followed by another period with above and below median informational overlap and rerun the portfolio analysis separately for each subsample. The results are reported in Table 9. Future returns are around 10 bp per month higher where the informational overlap is low, suggesting that new information is more likely to contribute to the return persistence than stale information.

Overall, the analysis in this section is consistent with the conclusion that companies can create sustainable price trends by rationing positive information and releasing it in a series of reports over a period of several months. It appears that investors' underreaction to the actual public information plays a weaker part in creating the return persistence effect than is commonly thought. Rather, investors are "guilty" only insofar as they are unable to foresee the nature of the forthcoming information or act on their forecasts.

7. Information Disclosures and Stock Risk

So far, the discussion has centered on the relationship between releases of private information and future stock returns. The results of this analysis are consistent with the view that information disclosed is unlikely to be a fair signal of the private information companies actually possess and that selective treatment of positive and negative information can result in temporary stock misvaluations. In this section, I pose a different question: how do private information releases depend on public information signals and on market conditions? Specifically, do firms release mostly good information when public signals are also good or do they treat their private information conservatively using it as insurance against future unanticipated public shocks? Instead of considering future returns from PIR-strategies, this section studies the contemporaneous relationship between PIR and public information and PIR and market performance and the implications of this relationship for measures of stock risk.

7.1 Stock Volatility

The link between the arrival of public news and the disclosures of private information cannot be directly tested since we cannot explicitly observe all public information (that effectively envelops information arriving from all sources but the company). Hence, my analysis will rely on the structure laid out in Section 3. Simply put, I assume that the total stock return over a period is a combination of the return attributable to private information disclosures and the return driven by the arrival of public news plus noise. Consider the following expansion of equation (1):

$$R_1 = \Delta Y_1 + PIR_1 - cD_0 = \Delta Y_1 + PIR_1 + c/(1-c)\chi_1 - c/(1-c)\Delta X_1 \qquad (4)$$

I now assume that PIR is not a function of χ but is a function of ΔY:

$$PIR_1 = f(\Delta Y_1) + \varepsilon_1 = b_Y \Delta Y_1 + \varepsilon_1 \qquad (5)$$

The direct estimation of this relationship is impossible since ΔY is unobservable. Therefore, I will try to infer the sign and the magnitude of b_Y from the two observable variables: *PIR* and *R*. I further assume that the arrivals of public information and private information are uncorrelated. This assumption amounts to saying that both new public information ΔY and new private information ΔX are unbiased signals of new total information.[10] Building on these assumptions I can estimate the nature of the relationship between *PIR* and ΔY.

The return can be rewritten as

$$R_I = (1 + 1/b_Y)PIR_I + \varepsilon'_I \tag{6}$$

where ε'_I incorporates all terms independent of PIR_I. We can now evaluate b_Y by regressing the observable variable R_I on the observable variable PIR_I. If $b_Y = 0$, meaning that PIR_I is independent of ΔY_I, the coefficient in front of PIR_I should be approximately 1. If $b_Y > 0$, meaning that the effect of new positive public information is enhanced by releases of positive private information, the coefficient in front of PIR_I should be higher than 1. Finally, if $b_Y < 0$, and the effect of new public information is mitigated by private information releases, we should expect the coefficient in front of PIR_I to be lower than 1.

Table 10 shows the results of the Fama-Macbeth regressions of R_T on PIR_T for both quarterly and semi-annual frequency. The coefficient on PIR_T, although positive and significant in some specifications, is substantially lower than 1. This finding is consistent with the view that companies use private information to countervail the effects of public signals thus weakening the relationship between PIR and return and smoothing the price path.

[10] Consider a world where this assumption is violated. By definition, the arrival of ΔX is not priced by the market since it represents private information that the market does not learn in the current period. However, if ΔX is correlated with ΔY then future return momentum arises mechanically without any intervention from the firm. Periods of high stock returns driven by high positive ΔY are followed by periods of high returns driven by the leakage of the excess X that accumulated from ΔX. However, this scenario is unlikely because it implies that neither ΔX nor ΔY is an unbiased signal of total new information. In fact, both understate total information. From the empirical perspective, it is important that a positive correlation between innovations in private and public information would induce a mechanical positive correlation between public signals and private information releases. Since I find the opposite result, my conclusions would only be strengthened by such a correlation structure.

However, this effect requires more careful analysis. First of all, it becomes difficult to interpret the results in Table 10 if we allow *PIR* to be both a function of ΔY and a function of χ. Second, although it is natural to expect that companies with bigger negative sensitivity of private disclosures to public news have lower stock volatility, the economic magnitude of this effect is unclear. Thus it becomes necessary to study the cross-sectional relationship between private-public information sensitivity and volatility. To test this relationship, I assume that the sensitivity of *PIR* to ΔY is stable for a given firm over time and thus can be estimated as

$$b_{Yj} = 1 \;/\; (avgR_j \;/\; avgPIR_j - 1)$$

where $avgR_j$ ($avgPIR_j$) is the average return (PIR) of stock j across all quarters of the sample. In other words, $avgR_j/avgPIR_j$ is the univariate estimate of the coefficient in front of PIR in the return equation for a given company. In the cross-section of all the companies in the sample, the mean (median) b_{Yj} is -0.23 (-0.09) and is statistically significant at 5% (t-statistic of 2.29). Of course, the significance of this result is affected by a potentially substantial error in the estimation of b_{Yj} which can also affect the accurateness of further tests. To mitigate this error and to ease the economic interpretation, I create a dummy variable Dpp_j that takes the value of 1 if company j is above median by b_{Yj} among all companies in the sample and 0 otherwise.

Next, I perform the regression analysis of stock volatility on *Dpp* and a set of control variables. I estimate stock volatility at annual frequency as the standard deviation of either raw or market-adjusted monthly returns within a year. The results of this analysis are reported in Table 11. The intercept in the first and fourth columns gives an average level of volatility for stocks with below-median private-public information sensitivity while the coefficient on *Dpp* measures the gap in the volatility between below- and above- median stocks. In all specifications, *Dpp* is positive and strongly significant. This confirms that companies with lower (more negative) sensitivity of private disclosures to public news have lower stock volatility. The economic effect is non-negligible: the average level of volatility of stocks with above-median b_Y is 11.8% (= 1.15%/9.77%) higher than that of stocks with below-median b_Y.

This result is important from two perspectives. First, it validates the approach and the logic of the model structure and the estimation procedure of b_Y. Indeed, if the value of b_Y were driven by pure noise, the relationship between *Dpp* and volatility would lack statistical significance. Second, these results help evaluate the economic effect of the countercyclical private information disclosures. Specifically, in the current sample of companies the volatility gap between firms with above- and below- median smoothing is about 12%.

7.2 Stock Beta

The classical asset pricing theory posits that stock volatility does not directly matter for rational investors holding well diversified portfolios. Therefore the volatility reduction techniques, if used at all, are not effective in wooing buyers unless they also reduce stock beta. Of course, the classical view has been comprehensively challenged in recent years and we can safely assume the existence of a sizable group of investors that would be attracted to lower volatility stocks, especially at the time of financial turmoil.

Nevertheless, I estimate the relationship between private information releases and market movements and investigate its effect on stock beta. The major shortcoming of the tests in the previous section is their reliance on the model structure to infer the unobservable state variable ΔY. However, market return is directly observable and can serve as a proxy of market-wide, although not company-specific, innovations in public information. Consider a company that conditions its private information releases on stock market fluctuations:

$$PIR_T = b_M M_T + \varepsilon_T \tag{7}$$

where M_T is the return on the market in period T. Such relationship is plausible. For example, companies can pursue aggressive stock growth during up-markets while dumping negative information in the down-markets, taking advantage of investors' myopia and imperfect information. Or vice versa, companies can attract risk-averse investors by offering them a better insurance again market downturns. Both of these strategies would affect beta and influence the risk premium that investors demand.

To link (7) and (1), I assume that each company's public information arrivals depend on the market via a linear model. This dependence reflects traditional exposure of each company's fundamentals to the market fluctuations:

$$\Delta Y_T = r_f + \beta_M M_T + \varepsilon_T \quad (8)$$

The following relationship between the stock and the market return can now be established:

$$R_T = r_f + (\beta_M + b_M) M_T + \varepsilon'_T \quad (9)$$

The last equation admits the following simple intuition: actual sensitivity of stock return to the market is a combination of the stock's fundamental beta (β_M) and its information beta (b_M). The latter can either amplify the company's market exposure if the company engages in bubble-building and bath-taking or reduce the market exposure if the company releases private information to mitigate the effects of market cycles.

It is advantageous that b_M can be estimated directly from the regression of *PIR* on M (7). First of all, the sign if this coefficient would indicate which of the two described strategies is more prevalent in the cross-section of companies in the sample. Second, this estimate can be interacted with market return M in regressions of R on M (9). This test would indicate whether the sensitivity of *PIR* to market cycles has a significant effect on stock beta.

Table 12 reports the results from both regressions. The first two columns of each block show the output of the OLS regression of PIR on the market return in that period defined as the return on the CRSP value-weighted index minus the risk-free rate reported in the Kenneth French s data library. The next two columns show the results of the OLS regression of stock returns on the market return and its interaction with the *avgPIR*/*avgM* ratio used as an estimate for b_M. The relationship between PIR and M is negative and is significant at the semiannual frequency. In the return regressions, the interaction between market return and the *avgPIR*/*avgM* ratio is significant at 10% at the quarterly and at 1% at the semi-annual frequency.

These results are directionally consistent with those documented in the previous section. In particular, companies appear to disperse more positive information when the market is in downturn. However, compared to the effect on volatility, the economic effects on beta are small: an increase in *avgPIR*/*avgM* ratio from 0 to 1 results in an increase in stock beta by 0.0043. These weak results are hardly surprising. First, market returns are hard to predict, making it difficult for companies to time their reports accurately. Second, market swings of considerable magnitude occur so rarely that any company will struggle to conceal its reserves of information until the right moment. Most of the information management strategies are likely to be short-term and play out over a horizon of months. Overall, the results in this section are directionally consistent with the price-smoothing behavior, yet they do not show a strong economic effect of private information disclosures on stock beta.

Conclusion

I study patterns of private information disclosures by top U.S. firms and relate them to return predictability phenomena and measures of stock risk. Using a dataset of over half a million corporate press releases, I construct a variable that proxies for the signed amount of information released by a company in a period and examine its relationship to future stock return. Among companies that release positive information, those that release more of it perform better in future periods. A portfolio long in companies from the top quartile and short in companies from the bottom quartile of released positive information earns an average holding return (3-factor alpha) of around 5.0% (7.1%) per year. Among firms that report negative news, those that release less negative information underperform those that release more: the long-short portfolio of the extreme quartiles delivers an annualized return of up to 4.1% and a 3-factor alpha of up to 4.3%. The first finding is consistent with the idea that companies tend to ration the delivery of their positive information to the market. As a result, the amount of private information released is proportional to the unreported amount and thus signals future stock growth. This effect contributes significantly to the Jegadeesh and Titman momentum which is entirely concentrated in stocks with high positive releases. The second result suggests that there is a significant variation in how objectively companies report bad news. The measure of released negative private information helps identify companies that are likely to underreport negative news and thus experience lower future returns. On average, releases of private information correlate negatively with the arrival of firm-specific public information, suggesting that firms time private information releases to mitigate the effect of public shocks on their stock price. Correspondingly, companies with an above-median negative correlation between the arrival of public news and private information releases have a 12% lower stock volatility. Future research can focus on incentives that make companies disclosure information in particular patterns. A comprehensive cross-sectional or event analysis can determine strategic drivers of selective disclosures as well as improve our understanding of the market reaction to information management techniques employed by corporate managers.

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Table 1. Summary statistics

Panel A. Main data

This panel shows summary statistics pertaining to the press-release (PR) and newswire (NW) data. The sample includes 519,865 press-release articles and 420,079 newswire articles covering all public U.S. companies that appeared among the top 1000 by market capitalization at any time (at the end of the year) between 1999 and 2008. The total number of company-days classified as event says is 256,796 for press releases and 167,300 for newswires.

PR events

	observation level	mean	median	min	max	st. dev.
total quarterly return (R)	company-quarter	2.26%	2.01%	-89.60%	423.81%	23.05%
cumulative return on event days	company-quarter	0.30%	0.00%	-68.06%	137.57%	7.46%
measure of released information (PIR_{PR})	company-quarter	0.34%	0.00%	-56.26%	177.01%	7.47%
number of event days in a period	company-quarter	7.51	3.00	0.00	60.00	10.10
number of articles	event day	2.02	1.00	1.00	312.00	3.55
number of words	article	738.96	536.00	5.00	73,010.00	1,092.25
daily market-adjusted return	positive event day	1.81%	1.17%	0.00%	103.54%	2.40%
daily market-adjusted return	negative event day	-1.67%	-1.10%	-75.88%	0.00%	2.23%

NW events

	observation level	mean	median	min	max	st. dev.
total quarterly return (R)	company-quarter	2.26%	2.01%	-89.60%	423.81%	23.05%
cumulative return on event days	company-quarter	0.26%	0.00%	-84.28%	288.99%	7.28%
measure of released information (PIR_{NW})	company-quarter	0.24%	0.00%	-50.81%	109.40%	6.03%
number of event days in a period	company-quarter	4.89	1.00	0.00	61.00	8.98
number of articles	event day	2.51	1.00	1.00	359.00	6.43
number of words	article	395.78	342.00	5.00	10,280.00	282.36
daily market-adjusted return	positive event day	1.85%	1.16%	0.00%	84.82%	2.42%
daily market-adjusted return	negative event day	-1.75%	-1.10%	-83.07%	0.00%	2.31%

Non-event days

	observation level	mean	median	min	max	st. dev.
daily market-adjusted return	positive non-event day	1.65%	1.03%	0.00%	139.29%	2.12%
daily market-adjusted return	negative non-event day	-1.53%	-0.99%	-65.96%	0.00%	1.87%

Panel B. News subjects

This panel shows top 5 subjects (as per Factiva classification) by impact and frequency of appearance for a randomly chosen 5% of PR and NW events. An article can be associated with multiple subjects in which case the article will count toward the frequency and impact for each subject it is associated with. Average daily return refers to the average market-adjusted return across all event days of that type.

PR events

positive events				**negative events**			
by occurrence		by average return magnitude		by occurrence		by average return magnitude	
subject	frequency	subject	avg daily return	subject	frequency	subject	avg daily return
Performance	31.03%	PPP/PFI *	7.73%	Funding/Capital	29.92%	Corporate Digest	-2.92%
Funding/Capital	29.22%	Audio-visual Links	3.11%	Performance	29.43%	PPP/PFI	-2.57%
Government Finance	15.94%	Money/Forex Markets	2.70%	Government Finance	15.77%	Equity Markets	-2.40%
New Products/Services	12.76%	Corporate Crime/Legal/Judicial	2.70%	New Products/Services	13.24%	Corporate Crime/Legal/Judicial	-2.32%
Management Issues	11.05%	Equity Markets	2.52%	Management Issues	11.64%	Existing Products/Services	-2.20%

NW events

positive events				**negative events**			
by occurrence		by average return magnitude		by occurrence		by average return magnitude	
subject	frequency	subject	avg daily return	subject	frequency	subject	avg daily return
Political/General News	65.08%	Equity Markets	6.43%	Political/General News	64.99%	People Profile	-4.88%
Regulation/Government Policy	14.52%	Performance	4.65%	Regulation/Government Policy	15.37%	Capacity/Facilities	-3.94%
New Products/Services	8.89%	Funding/Capital	3.75%	New Products/Services	7.27%	Money/Forex Markets	-3.90%
Performance	6.67%	Ranking	3.54%	Performance	6.76%	Output/Production	-3.79%
Product Safety	4.84%	Ownership Changes	3.23%	Product Safety	5.61%	Performance	-3.51%

* stands for "Public Private Partnership / Private Finance Initiative"

Table 2. Relationship between the amount of the released information and the company's media activity

This table shows how the signed amount of private information released PIR and the absolute amount of private information released |PIR| depend on the number of press releases (divided by 100), the fraction of event days in the quarter, and a set of cross-sectional firm characteristics. The regressions are OLS with time fixed effects. Standard errors are clustered at the firm level. T-statistics are given in parentheses.

	Dependent variable				Dependent variable			
Independent variable	PIR	PIR	PIR	PIR	| PIR |	| PIR |	| PIR |	| PIR |
numPRs	0.0132*** (2.98)	0.0097** (2.02)			0.0244*** (11.22)	0.0141*** (4.34)		
fraceventdays			0.0302*** (5.90)	0.0274*** (4.17)			0.2217*** (33.72)	0.2281*** (34.02)
size		-0.0006 (-0.37)		-0.0021* (-1.69)		-0.0034** (-2.22)		-0.0072*** (-6.34)
BtoM		0.0027 (0.74)		0.0014 (0.57)		0.0121*** (3.67)		0.0052** (2.27)
illiquidity		0.0003 (1.64)		0.0002* (1.70)		-0.0016*** (-8.05)		-0.0007*** (-6.82)
instownership		0.0053 (1.26)		0.0033 (1.34)		0.0017 (0.33)		0.0030 (1.41)
volume		0.0000*** (2.83)		0.0000*** (2.77)		0.0000*** (3.57)		0.0000*** (2.70)
leverage		-0.0004 (-0.11)		-0.0001 (-0.06)		-0.0102** (-2.08)		-0.0062** (-2.52)
infotransp		-0.0030** (-2.02)		-0.0019* (-1.93)		-0.0043** (-2.11)		-0.0031* (-1.83)
Fixed effects	time (quarter)	time (quarter)	time (quarter)	time (quarter)	time (quarter)	time (quarter)	time (quarter)	time (quarter)
Number of observations	21,553	17,371	33,525	25,849	21,553	17,371	33,525	25,846
R-sq	0.69%	1.28%	0.83%	1.28%	13.67%	17.33%	34.66%	35.33%

Table 3. Portfolio analysis based on the amount of private information released

This table shows the performance of portfolios formed on the basis of the amount of the reported information PIR. For each company-month I calculate PIR over the past 3 months (panel A) or the past 6 months (panel B). I split the sample into positive and negative PIR. Within each subsample, I sort stocks by PIR into four quartiles (each quartile is an equally weighted portfolio of stocks) and consider the portfolio long in the top quartile and short in the bottom quartile. This portfolio is held for 3, 6, or 12 months and then rebalanced. At any month, the return on the strategy is the average of returns of portfolios built in the last 3 months (panel A) or the last 6 months (panel B). Reported are the average monthly returns and 3-factor alphas. T-statistics are given in parentheses. The analysis is conducted for all stocks in the positive and negative PIR sample as well as separately for stocks with below- and above- median information transparency in the formation period. Sorting by PIR is done independently of the information transparency.

Panel A. Formation period: quarter

	negative PIR sample			positive PIR sample		
	3 months	6 months	12 months	3 months	6 months	12 months
Average monthly return on the long-short strategy						
whole sample	-0.0033***	-0.0028**	-0.0025*	0.0027**	0.0038**	0.0039**
	(-2.94)	(-2.40)	(-1.76)	(2.04)	(2.41)	(2.26)
below-median transparency	-0.0036***	-0.0030**	-0.0020	0.0050***	0.0056***	0.0054***
	(-3.05)	(-2.46)	(-1.34)	(3.08)	(3.12)	(3.20)
above-median transparency	-0.0027**	-0.0027*	-0.0026*	-0.0011	0.0014	0.0020
	(-2.15)	(-1.88)	(-1.82)	(-0.27)	(0.90)	(1.44)
3-factor monthly alpha of the long-short strategy						
whole sample	-0.0035***	-0.0032**	-0.0027*	0.0037**	0.0045**	0.0052***
	(-3.08)	(-2.47)	(-1.85)	(2.50)	(2.11)	(2.71)
below-median transparency	-0.0039***	-0.0033**	-0.0022*	0.0066***	0.0063***	0.0072***
	(-3.22)	(-2.22)	(-1.71)	(3.84)	(3.88)	(4.19)
above-median transparency	-0.0032***	-0.0030*	-0.0027*	0.0004	0.0021	0.0024*
	(-3.31)	(-1.74)	(-1.94)	(0.16)	(1.46)	(1.80)

Panel B. Formation period: half-year

	negative PIR sample			positive PIR sample		
	3 months	6 months	12 months	3 months	6 months	12 months
Average monthly return on the long-short strategy						
whole sample	-0.0026**	-0.0016	-0.0009	0.0024**	0.0039**	0.0041**
	(-2.10)	(-1.44)	(-1.07)	(2.09)	(2.45)	(2.35)
below-median transparency	-0.0028*	-0.0014	-0.0007	0.0053***	0.0057***	0.0058***
	(-1.91)	(-1.60)	(-0.97)	(2.77)	(3.00)	(3.39)
above-median transparency	-0.0019	-0.0017	-0.0008	-0.0015	0.0018	0.0023*
	(-1.48)	(-1.26)	(-0.82)	(-0.70)	(1.28)	(1.76)
3-factor monthly alpha of the long-short strategy						
whole sample	-0.0028**	-0.0015	-0.0011	0.0030**	0.0052***	0.0057***
	(-2.26)	(-1.36)	(-1.27)	(2.18)	(3.21)	(3.10)
below-median transparency	-0.0031**	-0.0019*	-0.0010	0.0063***	0.0066***	0.0070***
	(-2.15)	(-1.76)	(-1.14)	(3.40)	(3.51)	(3.74)
above-median transparency	-0.0019*	-0.0016	-0.0010	0.0010	0.0017	0.0028**
	(-1.48)	(-1.33)	(-1.37)	(0.76)	(1.36)	(2.02)

Table 4. Regression analysis of future return as a function of private information released
This table shows the results of the Fama-Macbeth regressions of stock return and stock PIR in quarter T+1 and on the amount of private information released by the company in quarter T and its interaction with the information transparency measure. The slopes are allowed to be different between negative and positive PIR periods. To fit a continuous piece wise linear regression, I define variables *PIRneg* and *PIRpos* as follows:

PIRneg = *PIR*, if *PIR* < 0 and 0 otherwise
PIRpos = *PIR*, if *PIR* ≥ 0 and 0 otherwise

T-statistics are given in parentheses. Newey-West correction with lag 3 is applied to standard errors.

Independent variable	Dependent variable			Dependent variable		
	next quarter return	next quarter return	next quarter return	next quarter PIR	next quarter PIR	next quarter PIR
PIRneg	-0.0467** (-2.17)	-0.1245*** (-2.64)	-0.1171** (-2.29)	-0.0113 (-1.45)	-0.0104 (-1.52)	-0.0207* (-1.74)
PIRpos	0.0990*** (2.88)	0.1404*** (3.07)	0.1851** (2.32)	0.0365** (2.42)	0.0475** (2.38)	0.0303** (2.12)
*PIRneg * infotransp*			0.0348 (1.16)			0.0732 (1.43)
*PIRpos * infotransp*			-0.1205** (-2.11)			-0.0615 (-1.05)
infotransp		-0.0003 (-0.10)	-0.0003 (-0.11)		-0.0015 (-1.65)	-0.0014 (-1.57)
size		-0.0192** (-2.63)	-0.0193** (-2.63)		0.0006 (0.56)	0.0005 (0.49)
BtoM		-0.0083 (-0.49)	-0.0081 (-0.47)		-0.0012 (-0.99)	-0.0014 (-1.13)
illiquidity		0.0020*** (2.95)	0.0020*** (2.91)		0.0003* (1.72)	0.0003 (1.67)
instownership		0.0078 (0.60)	0.0080 (0.61)		0.0025 (0.78)	0.0019 (0.61)
volume		0.0000* (1.92)	0.0000* (1.92)		0.0000** (2.36)	0.0000** (2.40)
Number of observations	32,412	24,971	24,971	31,881	24,525	24,525

Table 5. Long-short momentum portfolios conditional on the amount of private information released and its ratio to total return

This table shows average returns and 3-factor alphas of long-short momentum strategies built for the samples of companies with below- and above- median PIR (panel A) or below- and above- median PIR/R (panel B). In each month, stocks are separated into those with negative observation period return (losers) and positive observation period return (winners). For this analysis, the observation period is 6 months preceding the portfolio formation date. Both winners and losers are then sorted into two equal groups by released private information in the observation period (PIR) or the ratio of this measure to the stock return in the period (PIR/R) and four quartiles by the observation period return (R). The sorting on PIR or PIR/R is conducted independently of sorting by R. The long-short portfolio is defined as the portfolio long in the top performance quartile and short in the bottom performance quartile. This portfolio is held for 3, 6, or 12 months. At any month, the return on the strategy is the average of returns of long-short portfolios formed in the last 6 months. Reported are the average monthly returns and 3-factor alphas of the strategy. T-statistics are given in parentheses.

Panel A. Conditional on PIR

	negative R sample			positive R sample		
	3 months	6 months	12 months	3 months	6 months	12 months
Average monthly return on the long-short strategy						
below-median	-0.0011	-0.0018	-0.0015	0.0028	0.0024	0.0030*
PIR	(-0.84)	(-0.85)	(-1.15)	(1.36)	(1.16)	(1.92)
above-median	-0.0017	-0.0019	-0.0020	0.0055**	0.0047**	0.0027
PIR	(-0.25)	(-0.30)	(-0.71)	(2.07)	(2.00)	(1.41)
3-factor monthly alpha of the long-short strategy						
below-median	-0.0015	-0.0012	-0.0017*	0.0018	0.0026	0.0020
PIR	(-1.61)	(-1.53)	(-1.69)	(1.46)	(1.41)	(0.81)
above-median	-0.0013	-0.0016	-0.0015	0.0046**	0.0038**	0.0029*
PIR	(-1.04)	(-0.67)	(-1.15)	(2.47)	(2.31)	(1.84)

Panel B. Conditional on PIR/R

	negative R sample			positive R sample		
	3 months	6 months	12 months	3 months	6 months	12 months
Average monthly return on the long-short strategy						
below-median	-0.0011	-0.0016	-0.0018	0.0027	0.0021	0.0023
PIR/R	(-0.62)	(-0.74)	(-1.10)	(1.45)	(1.20)	(0.84)
above-median	-0.0013	-0.0010	-0.0017	0.0043**	0.0036**	0.0026**
PIR/R	(-0.36)	(-0.32)	(-0.71)	(2.35)	(2.26)	(2.57)
3-factor monthly alpha of the long-short strategy						
below-median	-0.0010	-0.0017	-0.0011	0.0024	0.0017	0.0025*
PIR/R	(-1.40)	(-1.46)	(-1.59)	(1.59)	(1.44)	(1.78)
above-median	-0.0015	-0.0012	-0.0019	0.0035**	0.0032**	0.0023*
PIR/R	(-1.21)	(-1.01)	(-1.21)	(2.32)	(2.17)	(1.89)

Table 6. Regression analysis of momentum and reversals

This table shows the results of the continuous piece-wise linear Fama-Macbeth regression of stock return in period T+1 on its return in period T interacted with PIR or PIR/R. Periods are either quarterly or semi-annual. Standard errors are Newey-West adjusted with lag 3 to account for possible autocorrelation of error terms. T-statistics are given in parentheses.

	Dependent variable				Dependent variable			
Independent variable	next quarter return	next quarter return	next quarter return	next quarter return	next half-year return	next half-year return	next half-year return	next half-year return
Rneg	-0.0432 (-1.21)	-0.0205 (-1.45)	-0.0594* (-1.83)	-0.0605 (-1.50)	-0.0187 (-0.28)	0.0010 (0.02)	-0.0392 (-0.82)	-0.0207 (-0.45)
Rpos	0.0915* (2.01)	0.0530 (1.37)	0.0758** (2.40)	0.0509 (1.29)	0.0804* (1.85)	0.0506 (1.14)	0.0666* (1.97)	0.0235 (0.53)
*Rneg * PIR*	-0.0605 (-0.32)	-0.0593 (-0.11)			-0.0975 (-1.01)	-0.0635 (-0.34)		
*Rpos * PIR*	0.1249* (1.77)	0.2106*** (2.65)			0.1935** (2.31)	0.2103*** (2.84)		
*Rneg * PIR/R*			0.0633 (0.33)	0.2091 (1.34)			-0.1405 (-0.66)	-0.1901 (-0.76)
*Rpos * PIR/R*			0.1034* (1.82)	0.2661** (2.11)			0.2604* (1.73)	0.4359*** (2.92)
PIR	-0.0379 (-0.97)	-0.0190 (-0.39)			-0.0054 (-0.17)	0.0082 (0.24)		
PIR/R			-0.0109 (-0.55)	0.0348 (1.58)			-0.1698 (-1.67)	-0.0979 (-1.04)
size		-0.0136* (-2.01)		-0.0141** (-2.10)		-0.0233** (-2.12)		-0.0231** (-2.20)
BtoM		-0.0109 (-0.70)		-0.0108 (-0.72)		-0.0149 (-0.44)		-0.0139 (-0.44)
illiquidity		0.0024*** (3.25)		0.0024*** (3.25)		0.0034** (2.31)		0.0038** (2.43)
instownership		0.0114 (0.97)		0.0121 (1.04)		0.0248 (1.12)		0.0296 (1.33)
volume		0.0000 (1.46)		0.0000 (1.42)		0.0000 (1.13)		0.0000 (1.10)
infotransp		-0.0016 (-0.51)		-0.0012 (-0.40)		0.0006 (0.09)		0.0007 (0.12)
Number of observations	32,412	24,971	32,381	24,971	16,018	12,365	16,005	12,365

Table 7. Future releases of information and profitability of PIR-strategies

This table reports the results of the portfolio analysis similar to that of Table 3. For this analysis, only those formation periods are considered that are followed by another period with the same sign of PIR. Both the positive and the negative PIR samples are further split into two subsamples depending on whether the next period's PIR is below or above median for the company across its whole time series of observations. Panel A (Panel B) reports profitability of the long-short PIR strategy for quarterly (semi-annual) periods.

Panel A. Formation period: quarter

	negative PIR sample			positive PIR sample		
	3 months	6 months	12 months	3 months	6 months	12 months
Average monthly return on the long-short strategy						
next period is below-median PIR	-0.0036** (-2.20)	-0.0030* (-1.77)	-0.0024 (-1.50)	0.0024** (2.11)	0.0033*** (2.68)	0.0029** (2.45)
next period is above-median PIR	-0.0031* (-1.84)	-0.0023 (-1.46)	-0.0018 (-0.98)	0.0042*** (3.43)	0.0050*** (3.62)	0.0054*** (3.20)
3-factor monthly alpha of the long-short strategy						
next period is below-median PIR	-0.0039** (-2.36)	-0.0029* (-1.94)	-0.0018 (-1.11)	0.0028** (2.37)	0.0037*** (2.90)	0.0035*** (3.25)
next period is above-median PIR	-0.0034** (-2.14)	-0.0021* (-1.69)	-0.0015 (-0.82)	0.0048*** (3.61)	0.0063*** (3.36)	0.0066*** (3.11)

Panel B. Formation period: half-year

	negative PIR sample			positive PIR sample		
	3 months	6 months	12 months	3 months	6 months	12 months
Average monthly return on the long-short strategy						
next period is below-median PIR	-0.0024** (-2.06)	-0.0026* (-1.82)	-0.0016 (-1.10)	0.0020** (2.01)	0.0028** (2.22)	0.0022** (2.26)
next period is above-median PIR	-0.0020 (-1.29)	-0.0017 (-1.27)	-0.0014 (-1.18)	0.0037*** (3.09)	0.0054*** (3.77)	0.0060*** (4.04)
3-factor monthly alpha of the long-short strategy						
next period is below-median PIR	-0.0029** (-2.18)	-0.0024* (-1.72)	-0.0013 (-0.80)	0.0026** (2.44)	0.0034** (2.26)	0.0030** (2.48)
next period is above-median PIR	-0.0025* (-1.84)	-0.0020 (-1.45)	-0.0012 (-0.96)	0.0045*** (3.12)	0.0066*** (3.40)	0.0069*** (3.68)

Table 8. Portfolio analysis based on the amount of information reported in newswires
This table shows profitability of long-short strategies built on the amount of information reported in newswires (Panel A) and profitability of momentum strategies conditional on the information reported in newswires (Panel B). This analysis follows the approach described in Table 3 (for Panel A) and Table 5 (for Panel B) but uses the measure of information distributed thorough newswires (NIR) instead of the measure of information released in press releases (PIR).

Panel A. Portfolio built on NIR

	negative NIR sample			positive NIR sample		
	3 months	6 months	12 months	3 months	6 months	12 months
Average monthly return on the long-short strategy						
formation period:	0.0015	0.0011	-0.0006	0.0022*	0.0024	0.0024
quarter	(0.53)	(0.61)	(-0.21)	(1.80)	(1.41)	(1.36)
formation period:	0.0019	0.0015	0.0014	0.0019	0.0023*	0.0020
half-year	(0.72)	(0.58)	(0.48)	(1.18)	(1.70)	(1.49)
3-factor monthly alpha of the long-short strategy						
formation period:	0.0013	0.0010	-0.0004	0.0025**	0.0026*	0.0022
quarter	(0.32)	(0.44)	(-0.30)	(2.03)	(1.70)	(1.18)
formation period:	0.0017	0.0015	0.0012	0.0020	0.0021	0.0017
half-year	(0.66)	(0.52)	(0.40)	(1.37)	(1.29)	(1.05)

Panel B. Momentum portfolios conditional on NIR

	negative R sample			positive R sample		
	3 months	6 months	12 months	3 months	6 months	12 months
Average monthly return on the long-short strategy						
below-median NIR	-0.0018	-0.0011	-0.0017	0.0035*	0.0033	0.0026
	(-0.99)	(-0.63)	(-0.85)	(1.88)	(1.59)	(1.26)
above-median NIR	0.0002	-0.0009	-0.0016	0.0039*	0.0038	0.0029
	(0.10)	(-0.44)	(-0.82)	(1.80)	(1.63)	(1.33)
3-factor monthly alpha of the long-short strategy						
below-median NIR	-0.0013	-0.0013	-0.0019	0.0029	0.0031	0.0024
	(-0.51)	(-0.73)	(-1.05)	(1.48)	(1.42)	(1.35)
above-median NIR	-0.0003	-0.0014	-0.0018	0.0032*	0.0033	0.0028
	(-0.24)	(-0.60)	(-0.92)	(1.78)	(1.29)	(1.20)

Table 9. Profitability of PIR strategies conditional on the informational overlap between consecutive periods

This table shows how profitability of PIR strategies depends on the similarity of the information released in the current and the next period. The similarity of informational content between the periods is measured as the number of common words contained in the current and the next period's press releases divided by the total number of words contained in these press releases. For each company, the sample is subdivided into observations where this measure is below and above median. Panel A (Panel B) reports profitability of the long-short PIR strategy for quarterly (semi-annual) periods.

Panel A. Formation period: quarter

	negative PIR sample			positive PIR sample		
	3 months	6 months	12 months	3 months	6 months	12 months
Average monthly return on the long-short strategy						
below-median informational overlap	-0.0034**	-0.0028**	-0.0026**	0.0030**	0.0040***	0.0042***
	(-2.50)	(-2.40)	(-2.11)	(2.33)	(2.80)	(3.14)
above-median informational overlap	-0.0029**	-0.0025**	-0.0022*	0.0022**	0.0031***	0.0033**
	(-2.27)	(-2.21)	(-1.90)	(2.10)	(2.59)	(2.09)
3-factor monthly alpha of the long-short strategy						
below-median informational overlap	-0.0038***	-0.0033**	-0.0029**	0.0035***	0.0047***	0.0058***
	(-2.66)	(-2.32)	(-2.39)	(2.70)	(3.26)	(3.03)
above-median informational overlap	-0.0031**	-0.0027*	-0.0026*	0.0031**	0.0037***	0.0045***
	(-2.25)	(-1.99)	(-1.74)	(2.48)	(2.91)	(2.62)

Panel B. Formation period: half-year

	negative PIR sample			positive PIR sample		
	3 months	6 months	12 months	3 months	6 months	12 months
Average monthly return on the long-short strategy						
below-median informational overlap	-0.0028**	-0.0019*	-0.0011	0.0026**	0.0044***	0.0041***
	(-2.05)	(-1.77)	(-0.83)	(2.12)	(2.87)	(2.84)
above-median informational overlap	-0.0020	-0.0013	-0.0008	0.0017*	0.0034**	0.0037**
	(-1.31)	(-1.17)	(-0.74)	(1.86)	(2.19)	(2.25)
3-factor monthly alpha of the long-short strategy						
below-median informational overlap	-0.0031**	-0.0023*	-0.0012	0.0032***	0.0055***	0.0061***
	(-2.33)	(-1.92)	(-0.69)	(2.81)	(3.68)	(3.53)
above-median informational overlap	-0.0024**	-0.0014	-0.0007	0.0025*	0.0046***	0.0050***
	(-2.15)	(-1.10)	(-0.41)	(1.79)	(2.84)	(2.90)

Table 10. Relationship between total return and return driven by private information releases
This table shows the results of the Fama-Macbeth regression of stock returns on the measure of private information released during the same period. Periods are either quarterly or semi-annual. T-statistics are given in parentheses. Standard errors are Newey-West adjusted with lag 3.

	Dependent variable		Dependent variable	
Independent variable	quarterly R	quarterly R	semi-annual R	semi-annual R
PIR	0.0481** (2.30)	0.0386 (1.56)	0.0801** (2.06)	0.0607* (1.82)
size		-0.0225** (-2.47)		-0.0420* (-2.06)
BtoM		-0.0076 (-0.44)		-0.0227 (-0.55)
illiquidity		0.0017** (2.21)		0.0042** (2.36)
instownership		0.0071 (0.47)		-0.0057 (-0.14)
volume		0.0000** (2.28)		0.0000* (1.97)
infotransp		-0.0010 (-0.35)		0.0009 (0.20)
Number of observations	33,525	25,754	17,150	13,131

Table 11. Relationship between stock volatility and sensitivity of private information released to public news
This table shows the results of the OLS regression of stock return volatility on the dummy indicating sensitivity of private releases to public news (D_{pp}). For each company this sensitivity is assumed constant over time and is estimated as $1/(avgR/avgPIR - 1)$ where *avgPIR* and *avgR* are average values of *PIR* and return for that company across all quarters in the sample. Dummy D_{pp} takes the value of 1 if the company is above median by the private-public sensitivity among all companies in the sample and 0 otherwise. Volatility is estimated from either raw or market-adjusted monthly returns within a year. Each observation is company-year. Standard errors are clustered at the firm level. T-statistics are given in parentheses.

Independent variable	Dependent variable			Dependent variable		
	volatility of raw monthly returns	volatility of raw monthly returns	volatility of raw monthly returns	volatility of market-adjusted monthly returns	volatility of market-adjusted monthly returns	volatility of market-adjusted monthly returns
Intercept	0.0977*** (57.23)	0.8183*** (17.61)		0.0900*** (58.69)	0.7760*** (17.99)	
D_{pp}	0.0115*** (3.77)	0.0091*** (2.76)	0.0085*** (3.81)	0.0121*** (4.06)	0.0095** (2.37)	0.0093*** (3.92)
size		-0.0411*** (-15.95)	-0.0255*** (-9.68)		-0.0386*** (-16.25)	-0.0255*** (-10.42)
BtoM		0.0006 (0.13)	-0.0021 (-0.50)		-0.0031 (-0.72)	-0.0029 (-0.71)
illiquidity		-0.0035*** (-11.13)	-0.0011*** (-3.23)		-0.0035*** (-11.85)	-0.0014*** (-4.26)
instownership		-0.0492*** (-5.76)	0.0086 (0.88)		-0.0562*** (-7.14)	-0.0014 (-0.15)
volume		0.0000*** (7.21)	0.0000*** (6.68)		0.0000*** (7.13)	0.0000*** (6.73)
infotransp		-0.0006 (-0.39)	0.0002 (0.13)		-0.0010 (-0.77)	-0.0004 (-0.31)
Fixed effects	NO	NO	time (year)	NO	NO	time (year)
Number of observations	8,437	6,734	6,734	8,437	6,734	6,734
R-sq	0.49%	18.68%	32.85%	0.57%	18.49%	32.55%

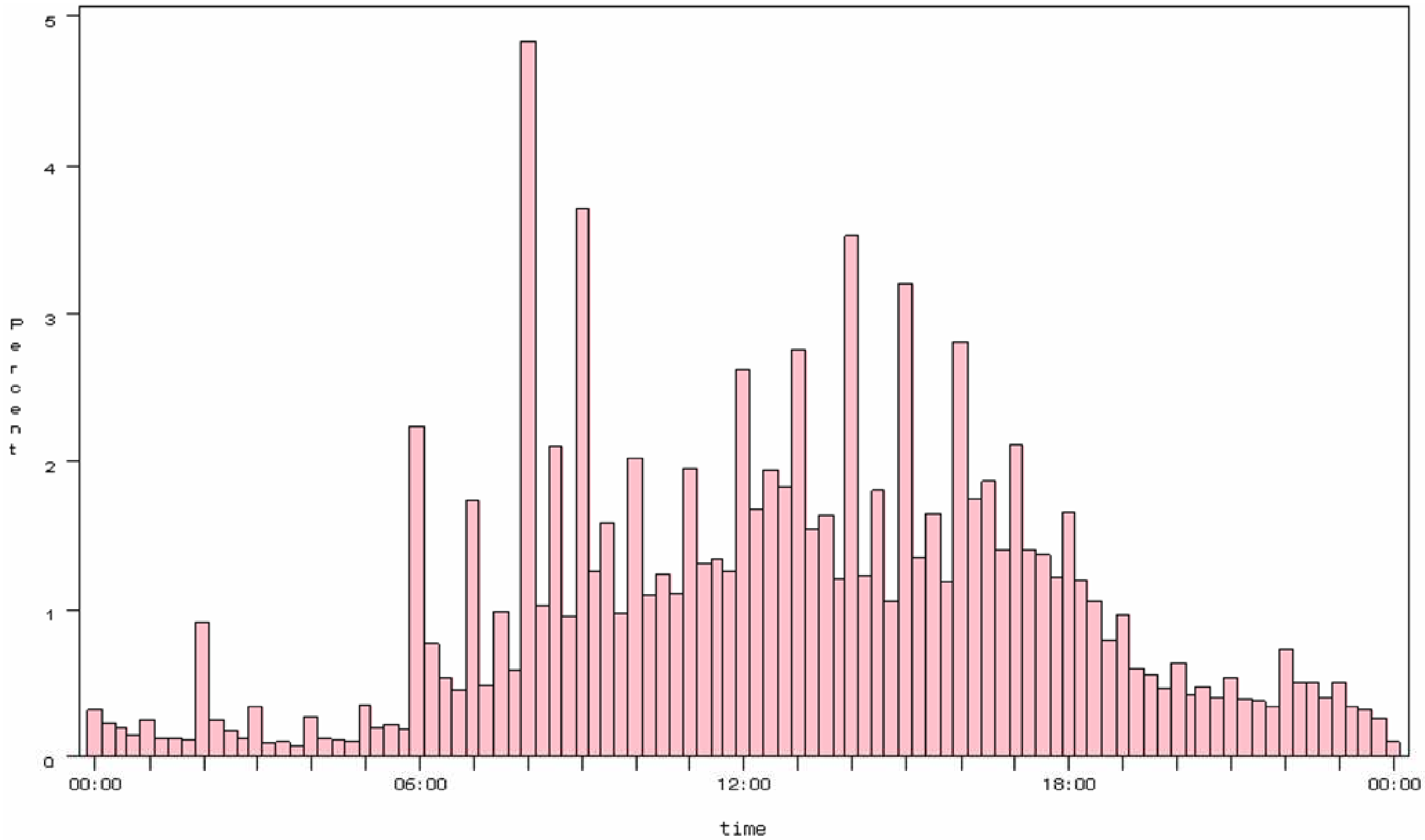
Table 12. Sensitivity of stock returns to the market and the role of private information releases

This table combines two regressions that connect private information releases to the return on the market index. First two columns of each block show the output of the OLS regression of PIR on the market return in that period. Market return is the return on the CRSP value-weighted index minus the risk-free rate reported in the Kenneth French's data library. The next two columns show the results of the OLS regression of stock returns on the market return and its interaction with the PIR/R ratio. Periods are either quarterly or semi-annual. T-statistics are given in parentheses. Standard errors are Newey-West adjusted with lag 3.

	Dependent variable				Dependent variable			
Independent variable	quarterly PIR	quarterly PIR	quarterly R	quarterly R	semi-annual PIR	semi-annual PIR	semi-annual R	semi-annual R
Intercept	0.0034*** (8.30)	0.0099 (0.74)	0.0368*** (32.33)	-0.3012*** (-9.11)	0.0119*** (5.30)	0.1215*** (3.19)	0.0716*** (29.27)	-0.3867*** (-5.54)
M	-0.0140* (-1.88)	-0.0091 (-0.74)	1.0492*** (82.53)	0.9928*** (72.09)	-0.0898*** (-3.49)	-0.0581* (-1.83)	0.9188*** (42.23)	0.7517*** (32.32)
*M * avgPIR/avgM*			0.0018* (1.84)	0.0020* (1.90)			0.0043*** (3.74)	0.0056*** (4.15)
avgPIR/avgM			0.0000 (0.60)	0.0000 (0.72)			0.0001 (0.90)	-0.0001 (-0.57)
size		-0.0009 (-1.19)		0.0214*** (10.98)		-0.0079*** (-3.53)		0.0329*** (8.00)
BtoM		0.0041*** (2.95)		-0.0752*** (-21.87)		0.0103*** (2.70)		-0.1653*** (-23.69)
illiquidity		0.0001 (0.80)		0.0056*** (21.20)		-0.0003 (-1.11)		0.0073*** (13.09)
instownership		0.0041 (1.57)		-0.0091 (-1.39)		-0.0053 (-0.71)		-0.0528*** (-3.89)
volume		0.0000*** (10.21)		0.0000*** (-7.23)		0.0000*** (13.28)		0.0000*** (-7.61)
infotransp		-0.0020** (-2.04)		0.0046* (1.90)		-0.0048* (-1.76)		0.0053 (1.05)
Number of observations	33,525	25,849	34,212	26,415	17,150	13,249	17,150	13,249
R-sq	0.00%	0.62%	16.61%	21.12%	0.12%	1.88%	9.48%	16.37%

Figure 1. Distribution of press-release articles (PR) and newswire articles (NW) by time of day
These histograms show how PR and NW articles are distributed throughout the day. The distribution is given before filters are applied and the articles are assigned to days on which the market is likely to react to the news.

Panel A. Distribution of press releases



Panel B. Distribution of newswires

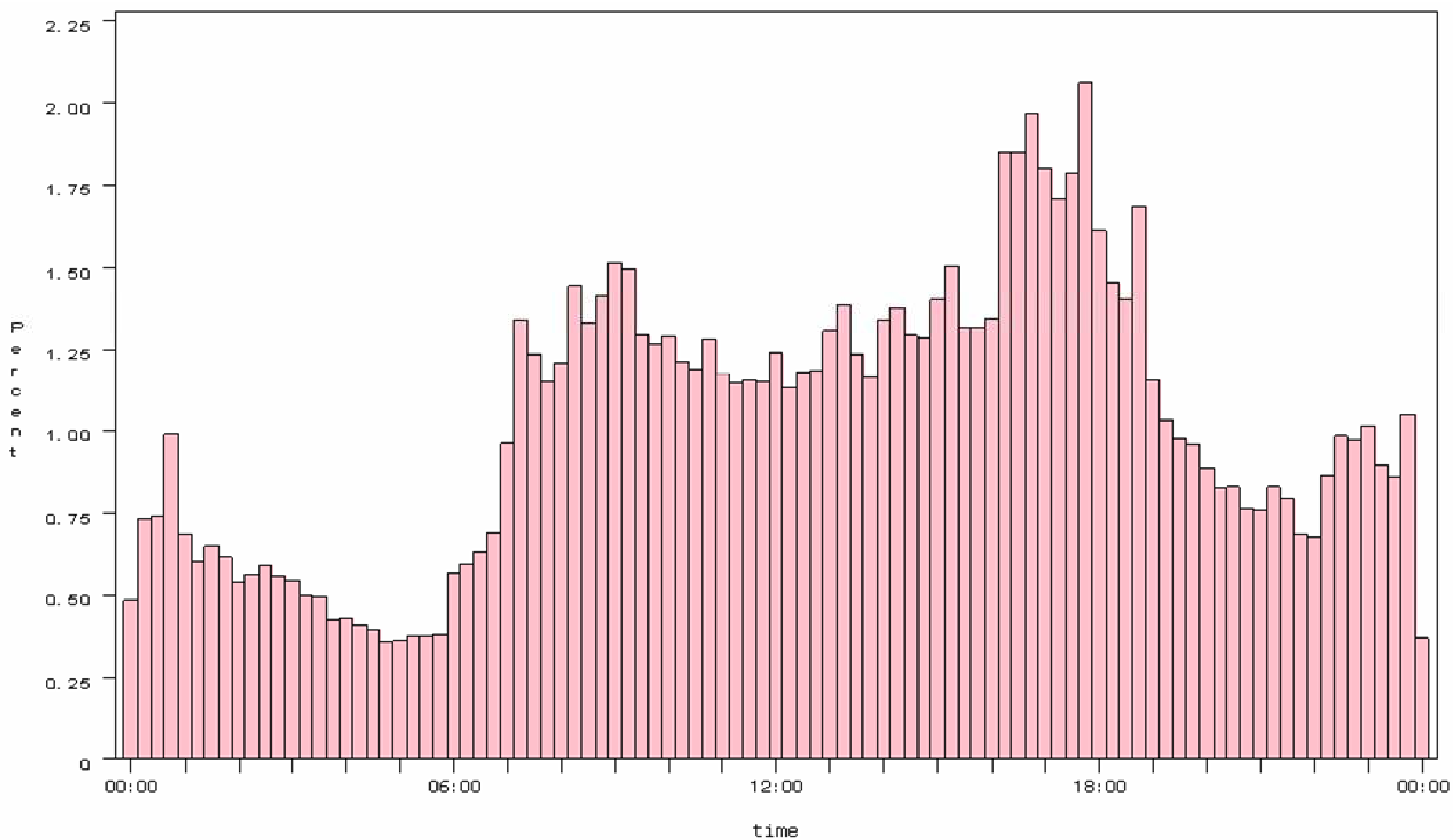
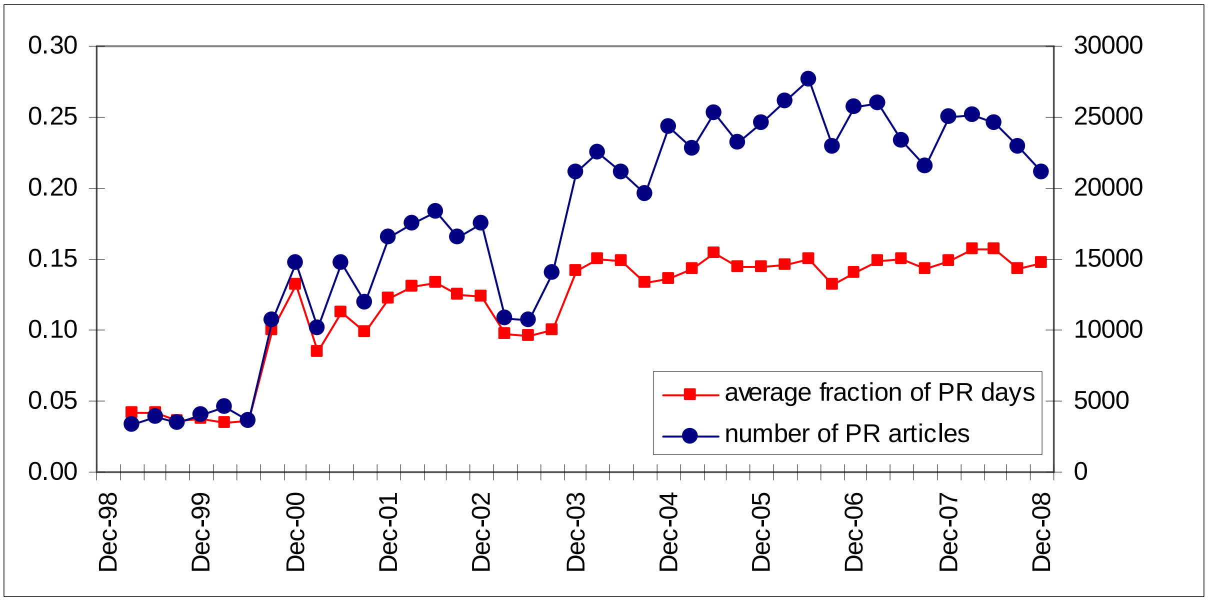
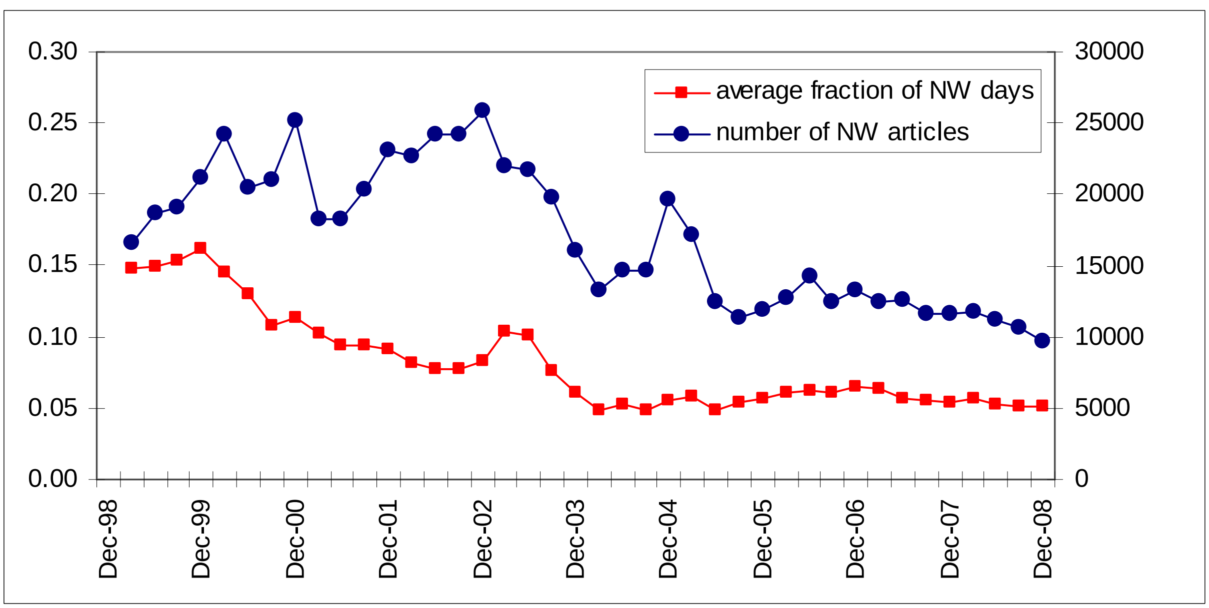


Figure 2. Historical press-release (PR) and newswire (NW) media activity
These graphs show how the number of reports and the fraction of event-days in a quarter evolved over time

Panel A. Historical PR activity



Panel B. Historical NW activity



Appendix 1. Model solution for the case $PIR_T = b\chi_T + \varepsilon_T$

Need to derive $\mathrm{E}[R_2|PIR_1]$

$R_2 = \Delta Y_2 + PIR_2 - cD_1$

$PIR_2 = b\chi_2 + \varepsilon_2 = b(-D_1 + \Delta X_2 + cD_1) + \varepsilon_2$

Thus,

$R_2 = \Delta Y_2 + b\Delta X_2 + \varepsilon_2 - (c + b - bc)D_1$

Therefore, since both ΔY_2 and ΔX_2 are independent of PIR_1 and, as stated in the model, $\mathrm{E}[\varepsilon_t] = 0$

$\mathrm{E}[R_2|PIR_1] = \mathrm{E}[\Delta Y_2] + b\mathrm{E}[\Delta X_2] - (c + b - bc)\mathrm{E}[D_1|PIR_1]$

Now,

$\mathrm{E}[D_1|PIR_1] = PIR_1 - \mathrm{E}[b\chi_1|PIR_1]/b$

In further notation μ_A and V_A stand for unconditional expected value and variance of variable A, respectively

Assuming normal distribution of all variables and recalling that $PIR_1 = b\chi_1 + \varepsilon_1$, we can calculate $\mathrm{E}[b\chi_1|PIR_1]$ from the projection theorem:

$$\mathrm{E}[b\,\chi_1\,|\,PIR_1] = b\,\mu_{\chi_1} + \frac{b^2 V_{\chi_1}}{b^2 V_{\chi_1} + V_\varepsilon}(PIR_1 - b\,\mu_{\chi_1})$$

Recall that

$\chi_1 = (1 - c)X_0 + \Delta X_1$

Assuming that ΔX_2 is independent of X_0, we get

$$\mu_{\chi_1} = (1-c)\,\mu_{X_0} + \mu_{\Delta X}$$

$$V_{\chi_1} = (1-c)^2 V_{X_0} + V_{\Delta X}$$

Aggregating all the results gives

$$E[R_2|PIR_1] = E[\Delta Y_2] + bE[\Delta X_2] - (c + b - bc)E[D_1|PIR_1] =$$

$$\mu_{\Delta Y} + b\,\mu_{\Delta X} - (c+b-bc)\left(\left(1 - \frac{b((1-c)^2 V_{X_0} + V_{\Delta X})}{b((1-c)^2 V_{X_0} + V_{\Delta X}) + V_\varepsilon}\right) PIR_1 - \left(1 - \frac{b^2((1-c)^2 V_{X_0} + V_{\Delta X})}{b^2((1-c)^2 V_{X_0} + V_{\Delta X}) + V_\varepsilon}\right)((1-c)\,\mu_{X_0} + \mu_{\Delta X})\right)$$

After we impose the following natural assumptions

$\mu_{X_0} = 0$

$\mu_{\Delta X} = 0$

$\mu_{\Delta Y} = 0$

the expression will simplify to

$$(c+b-bc)\left(\frac{b((1-c)^2 V_{X_0} + V_{\Delta X})}{b^2((1-c)^2 V_{X_0} + V_{\Delta X}) + V_\varepsilon} - 1\right) PIR_1$$

If we assume that none of the companies are mispriced at the beginning of period 1, the expression will simplify to

$$(c+b-bc)\left(\frac{b\,V_{\Delta X}}{b^2 V_{\Delta X} + V_\varepsilon} - 1\right) PIR_1$$